ESSAYS ON AGRICULTURAL COMMODITY MARKETS

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Glossary

AgriTR Index	Bloomberg Agriculture Total Return Index
ARCH model	Autoregressive Conditional Heteroscedasticity model
ASU	Accounting Standard Update
BMA	Bayesian Model Averaging
CTA	Colombo Tea Auction
CV	Coefficient of Variation
ECM	Error Correction Model
ETC	Exchange-traded commodity
ETF	Exchange-traded fund
ETN	Exchange-traded note
FAO	Food and Agriculture Organization
FAS	Financial Accounting Standard
FASB	Financial Accounting Standards Board
FAT	Funnel Asymmetry Test
FE model	Fixed Effect model
GARCH model	Generalized Autoregressive Conditional Heteroscedasticity model
GMVP	Global Minimum Variance Portfolio
IAS	International Accounting Standard
IASB	International Accounting Standards Board
IETC	Inverse exchange-traded commodity
IFRS	International Financial Reporting Standard
LETC	Leveraged exchange-traded commodity
ML	Maximum Likelihood

MS Regression	Markov switching regression
MV hedge ratio	Minimum variance hedge ratio
OLS	Ordinary Least Squares
PEESE	Precision Effect Estimation with Standard Errors
PET	Precision Effect Test
PIP	Posterior Inclusion Probability
RE model	Random Effect model
SE	Standard error
TE	Tracking error

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Chapter One

Introduction

The past decade has drastically changed the structure and the composition of agricultural commodity markets. After 2000, commodity markets received large inflows of funds from institutional investors (Basak and Pavlova, 2016; Domanski and Heath, 2007).[1] According to Irwin and Sanders (2011), commodity investment has increased from $15 billion in 2003 to $250 billion in 2009. Furthermore, agricultural commodity markets became more accessible to investors after the introduction of index instruments on commodities such as exchange-traded commodities and index funds. This financialization process connected the agricultural commodity markets with financial markets while raising the popularity of commodity investments.

During the period of the financial crisis in 2008 and 2009, investors recognized the stringent need to expand their portfolios beyond investing in traditional investment assets. In this regard, agricultural commodities provided some appealing investment alternatives for the investors. Therefore, commodities became widely popular as an investment asset among different investors. Adams and Gluck (2015) argue that commodities have become an investment asset class for institutional investors.

Moreover, the agricultural commodity market has experienced drastic price bubbles in last decades. This high volatility in commodity prices has led to an ongoing debate where some researchers argue that the fundamental reasons (i.e. demand and supply related reasons) are at the core of this volatility (Krugman, 2008; Pirrong, 2008; Sanders and Irwin, 2010; Smith, 2009) whereas others argue that this speculative bubble is driven by the large volume of investments in index instruments (Liu, Filler and Odenning, 2013; Masters, 2008). Despite of

[1] Please note that the references of chapter one are included in the reference list of chapter two.

the numerous academic studies analysing this research question, the issue remains unsolved. Furthermore, there is no any guarantee that the world will not face more booms and busts in agriculture commodity prices in the future as well.

On a separate note, agricultural commodity markets parallel to the food industry have now become considerably more important due to several reasons. According to Food and Agriculture Organization (FAO) of the United Nations[2], the world population will reach approximately 9.7 billion by 2050. Furthermore, the urbanization rate is also increasing. At present about 55 percent of the world population is located within urban environments. FAO estimates that food production requires an increase of 60 percent by 2050 in order to cater to rising food demand due to increasing population. The increase in the household income due to urbanization will also increase the demand for food and hence, the demand for agricultural commodities.

However, it is important to understand that the level of financialization is different from commodity to commodity and from market to market. Simultaneously, the behaviour of commodities has changed after the financial crisis along with the financialization process. These markets will still continue to evolve in the future either by creating innovative financial assets on new agricultural commodities or by modifying the existing financial assets on agricultural commodities. Due to this increased importance, changing structure and the high popularity of agricultural commodities, there is a high demand to conduct more research on these markets.

Accordingly, this study examines three different aspects of the agricultural commodity markets which have rarely been studied by previous researchers. First, it studies the design and performance of a recently introduced financial instrument in agricultural commodities. Second, it conducts a structural analysis of an existing agricultural market to analyse its readiness for

[2] Please refer to http://www.fao.org/faostat/en/#data for the details.

the financialization process. Third, it examines the extent to which the existing futures contracts serve the expected level of purpose required by the regulations. The next chapters in this thesis are therefore organized as follows.

The second chapter conducts an extensive analysis of an increasingly popular asset class, namely, exchange-traded commodities (ETCs). The introduction of index investing on agricultural commodities opens up different avenues for investors to gain the exposure to this market. ETCs provide exposure either to a single commodity index or to a multi-commodities index. This first chapter examines whether the tracking error of these ETCs is time varying depending on the volatility of the underlying agricultural commodity prices. Furthermore, it investigates whether the characteristics of a fund will affect its tracking performance differently between high- and low-volatility periods of the underlying commodity prices.

The third chapter examines the feasibility of introducing a derivative contract on a new agricultural commodity. Tea is one of the most popular beverages in the world. Its consumption exceeds the consumption of milk, coffee and orange juice. Despite its importance, tea is not yet considered a commodity in financial markets and hence there is no derivative contracts on tea. This chapter contributes to the existing literature in three ways. First, it contributes by providing a detailed overview of the structure of the oldest and the largest single origin tea market in the world. Second, the chapter answers the question of whether it is feasible to introduce a derivative contract on tea that would be beneficial for tea market participants. Finally, it examines the diversification benefits of tea as an investment asset in the portfolio of an average investor.

The fourth chapter reviews a novel research question related to derivative accounting practices. Derivatives on commodities are mainly popular among producers as a tool for hedging their exposure to price risk. When a company trades derivative, the accounting standard provides a guideline regarding how these transactions should be recorded in financial statements and regarding the level of disclosure required. There is a lack of empirical evidence to support the appropriateness of the derivative accounting standard in the existing literature. Therefore, this study questions the suitability of establishing a common threshold level of hedge effectiveness for all types of hedges and for all types of assets. Using a sample of minimum variance hedge ratio estimates collected from a selected set of existing studies, this study intends to provide an answer to this question by analysing this data using meta-analysis methodology.

Chapter five finally provides an overall summary of the findings of this thesis. This chapter highlights the practical importance of these findings for the investors, for the producers, for the regulators and for the policy makers of these markets.

Chapter Two

Is The Tracking Error Time Varying? Evidence from Agricultural ETCs

2.1. Introduction

Before the 2000s, commodity markets were largely segmented, and commodity investments were mainly used by commercial traders to hedge their exposure to the price risk of commodities. With the empirical evidence on the negative or zero correlation structure of commodities with traditional investment assets (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006), investors recognized the potential diversification benefits of investing in commodities. Thereafter, commodities (including agricultural commodities) gained rising popularity as an asset class in portfolios along with other traditional assets, such as stocks and bonds.[3] This popularity was fuelled by large investment flows made by institutional investors into the commodity markets[4] (Basak and Pavlova, 2016; Domanski and Heath, 2007) and with the emergence of index-based investment instruments, namely, exchange-traded funds (ETFs) (Tang and Xiong, 2012).

An exchange-traded commodity (ETC) is an exchange-traded investment product providing exposure to either a single-commodity index or to a multi-commodities index (Fassas, 2014). An ETF in Europe cannot provide the exposure to a single commodity only as it requires a certain degree of diversification to comply with the Undertakings for Collective Investments of Savings (UCITS)[5]. Therefore, ETCs are structured as debt instruments and

[3] Jensen, Johnson and Mercer (2000) conclude that adding commodities allowed investors to achieve a higher efficient frontier. Conover et al. (2010) find that by adding at least 5% of commodity exposure to a portfolio reduces the risk of that portfolio but does not increase the portfolio's return.

[4] Institutional investors were searching for alternative assets to reduce the risk of investing only in traditional assets, such as equity and bonds. Investing in a basket of commodities through a commodity index fund became the most popular strategy of investment due to the potential diversification benefits of commodities and low cost of investment.

[5] UCITS is the regulatory framework for an investment vehicle that can be marketed across the European Union. This regulation allows only the development of products tracking diversified commodity indices and does not allow ETFs providing exposure for a single commodity only. As a solution to this problem, the issuers introduced ETCs as debt instruments under the European Prospectus Directive. Please refer to Marszk (2017) for further details.

secured by collateral, whereas ETFs are considered as equity instruments. The ETC fund manager passively replicates the performance of an underlying commodity index and aims to provide a return similar to the underlying index. ETCs, being exchange traded, have become easily accessible, highly transparent and liquid instruments. They provide exposure to the commodity markets at a low cost- markets that are otherwise costly to invest in directly due to the high costs of storage. These characteristics of ETCs enhanced their popularity as an investment asset.

The world's first distinct ETC trading platform was established by the London Stock Exchange in 2004. As per the Bloomberg statistics (as at December 2018), there are 786 ETCs, 211 ETFs and 198 exchange-traded notes (ETNs) on commodities. These statistics suggest that ETC is the most popular fund type for commodities. There are 218 ETCs on agriculture (including livestock), which is second only to the number of ETCs on energy (239). Furthermore, out of these 786 commodity-based ETCs, 99 percent of the funds are primarily traded in European exchanges located in Germany, Luxembourg, Switzerland and the United Kingdom. Morningstar in 2017 predicted that the assets under management of the European exchange-traded products would reach 1 trillion euros by 2020.[6]

However, recent studies find a gradual change in the correlation structure between commodities and other investment assets because of this rise in the cash flow to index investment instruments in commodities (Basak and Pavlova, 2016; Silvennoinen and Thorp, 2013; Tang and Xiong, 2012). Specifically, Jensen and Mercer (2011) find that agricultural commodities are negatively correlated with stocks, treasury bonds and treasury bills during the period from 1970 to 1989. However, these correlations with agricultural commodities become

[6] This information is extracted from a report issued by Morningstar titled 'A guided tour of the European ETF marketplace – 2017'.

positive in the later period from 1990 to 2009. It is evident that the financialization of commodity markets has changed the structure of this market during past decades.

Furthermore, agricultural commodity markets experienced significant price increases in the 2007/2008, 2010/2011 and 2012/2013 periods. These price increases coincided with the popularity of index investment in agricultural commodities (Cheng and Xiong, 2014). Therefore, researchers argue this speculative bubble in agricultural commodity prices was driven by the large volume of index investments in commodities (Basak and Pavlova, 2016; Liu, Filler and Odenning, 2013; Masters, 2008). This high volatility in agricultural commodity prices possibly challenges ETC fund managers in tracking the performance of the underlying index. As a result, agricultural ETCs may not be able to entirely replicate the performance of the benchmark index during these high-volatility periods. Therefore, motivated by the fact that agricultural commodity prices have been highly volatile, this study aims to identify whether the tracking performance of agricultural ETCs will be different between high- and low-volatility periods.

The agricultural commodity markets have undergone another structural change since the early 2000s. Adjemian, Saitone and Sexton (2016), MacDonald et al. (2004) and Peterson (2005) reveal that agricultural markets have now become highly concentrated due to the increased coordination between farmers and processors. This high concentration creates thinly traded agricultural commodity markets.[7] The concern related to a thinly traded market is that it creates excess volatility in prices (Peterson, 2005). Therefore, agricultural ETCs are likely to have a high level of tracking error (TE) when there is a high volatility in prices.

This increasing popularity of ETCs in the European region and the changing structure of agricultural commodity markets in general enhanced the importance of conducting more

[7] Anderson et al. (2007) define a thinly traded market as a market in which the number of transactions over a given period of time is insufficient to ensure efficient price discovery process in the market. Adjemian et al. (2016) define a thinly traded market as a market with few buyers, low trading volume and low liquidity.

research studies on agricultural ETCs. Therefore, this study aims to fulfil this need by conducting an extensive study on the tracking performance of European agricultural ETCs. Accordingly, this study contributes to the literature in three ways.

First, the quality of a passively managed ETC will depend on its ability to replicate the underlying index as closely as possible. Previous studies have analyzed how the return of an ETF differs from the return of its benchmark index. Those previous studies have concluded that ETFs tracking equity, debt, sector, domestic and international indices do not replicate the underlying index precisely.[8] This study is unique because it includes a large sample of European agricultural ETCs and investigates the performance of these funds extensively.[9]

Second, this study adopts a different methodology compared with previous studies in that it examines the performance of ETCs during the entire sample period and tests whether there is a significant difference in the tracking performance of ETCs between high- and low-volatility periods of agricultural commodity prices. I did not find previous empirical evidence analysing this time varying behaviour of agricultural ETCs. Finally, this study investigates whether or not this tracking performance is persistent over time.

Third, the analysis of this research assesses the difference in tracking performance of agricultural ETCs based on fund characteristics, such as replication strategy and level of leverage.[10] Agricultural ETCs mainly create exposure to commodity markets by using synthetic replication strategy, i.e. using either futures contracts or swap contracts on commodities instead

[8] Blitz and Huij (2012), Chu (2011), Drenovak, Urosevic and Jelic (2014), Jares and Lavin (2004), Johnson (2009), Milonas and Rompotis (2006), Rompotis (2009) and Shin and Soydemir (2010) find that ETFs either underperform or over perform the underlying index.

[9] To the best of my knowledge, only Dorfleitner, Gerl and Gerer (2018) investigate the tracking performance of ETCs, but they focus only on the German ETC market. In addition, Aroskar and Ogden (2012) examine the performance of commodity ETNs, whereas Guo and Leung (2015) and Rompotis (2016) investigate the tracking performance of commodity ETFs.

[10] Previous literature provide evidence that tracking error is affected by the fund size (Grinblatt and Titman, 1989; Frino et al., 2004), expense ratio (Charupat and Miu, 2013; Elton et al., 2002; Frino and Gallagher, 2001), liquidity of the underlying stock (Osterhoff and Kaserer, 2016), cost of rebalancing (Gastineau, 2002) and bid-ask spread (Delcoure and Zhong, 2007; Milonas and Rompotis, 2006).

of investing in the physical commodity itself. Previous studied find that synthetic replication has affected negatively the tracking ability of ETFs (Drenovak and Urosevic, 2010; Fassas, 2014; Guedj, Li and McCann, 2011; Naumenko and Chystiakova, 2015; Rompotis, 2016). Hence, it is reasonable to expect this synthetic replication in agricultural ETCs will also generate a high level of TE. In addition, I examine whether the tracking performance based on replication strategy will be different between high- and low-volatility periods of the underlying agricultural prices.

The leveraged exchange-traded commodity (LETC) is another innovation of ETCs. LETCs are similar to ETCs, but their goal is to replicate the return of an underlying commodity index in either a positive (leveraged) or negative (inverse) multiple. LETCs use positive multiples such 2X, 3X and negative multiples such as -1X, -2X and -3X. These funds attempt to maintain the desired level of leverage within a one day holding period by daily rebalancing the fund. Due to the difficulty of this dynamic rebalancing, these funds are likely to either underperform or over perform the return target of the fund. In the sample of ETCs in this study, there are both leveraged and non-leveraged ETCs. These agricultural LETCs are also expected to generate a higher TE compared with non-leveraged agricultural ETCs. Finally, I examine whether there is a tracking performance difference between leveraged and non-leveraged ETCs in this sample.

According to the results, European agricultural ETCs generate a high level of TE during high-volatility periods of commodity prices. However, there is no evidence to conclude that TE is persistent. Furthermore, synthetic replication and leverage both lead to high tracking deviations in agricultural ETCs.

The remainder of this chapter is organized as follows. Section 2.2 provides an overview of the previous related literature. Section 2.3 describes the data and summarizes the descriptive statistics of commodity returns and TEs. Section 2.4 discusses the methods adopted to identify the commodity price cycles and presents subsequent findings. Section 2.5 presents the empirical results on the tracking performance of agricultural ETCs. Section 2.6 discusses the results on the persistence of TE. Finally, Section 2.7 summarizes and concludes the paper.

2.2. Literature Review

2.2.1. TE in exchange-traded products

There are several empirical studies providing evidence for both the existence and non-existence of TE in ETFs. Those studies provide inconclusive results regarding the tracking performance efficiency of these funds. Previous studies find TE in American, Asian and European ETFs (Shin and Soydemir, 2010), in Hong Kong ETFs (Chu, 2011; Johnson, 2009), in Malaysian and Taiwanese ETFs (Johnson, 2009), in German ETFs (Osterhoff and Kaserer, 2016), in Swiss ETFs (Milonas and Rompotis, 2006) and in ETFs on emerging market indices (Rompotis, 2015). In contrast, Gallagher and Segara (2006) conclude that Australian ETFs track their benchmark indices better compared with off-market index managed funds. Harper, Madura and Schnusenberg (2006) find uniformly negative but not significant TE in ETFs on foreign markets. Buetow and Henderson (2012) find no significant TE on 845 ETFs on equity, fixed income, preferred stocks, real estate and diversified sectors.

With respect to commodities, there is a limited number of empirical studies analysing tracking performance. Guo and Leung (2015) analyze the performance of 23 leveraged ETFs investing in gold, silver, oil and building materials and find most of these funds underperform their benchmark index. However, Aroskar and Ogden (2012) conclude that commodity-based iPath ETNs perform well in tracking the benchmark index. Dorfleitner, Gerl and Gerer (2018) examine the pricing efficiency of ETCs traded on the German market. They conclude that German ETCs are more likely to trade at a premium on their theoretical price. This limited attention of researchers on analysing the tracking performance of agricultural ETCs motivated me to conduct this study.

Furthermore, existing literature describes different factors that affect the magnitude of this TE. Theoretically, the higher the management fee or the expense ratio, the larger would be the TE (Elton et al., 2002; Rompotis, 2006; 2011). On a separate note, Frino et al. (2004) find that TE is significantly affected by the changes in index composition arising due to share issuances, share repurchases and spin-offs. These factors will increase the TE of ETFs due to the high transaction cost involved in changing the index composition. Furthermore, Elton et al. (2002) and Frino et al. (2004) show that the TEs of ETFs can be explained by the accrual of dividends on the stocks included in the benchmark index.

The previous studies provide further evidence that the return volatility of the underlying index (Rompotis, 2006) and equity market conditions (Qadan and Yagil, 2012; Wong and Shum, 2010) also affect the tracking performance of ETFs. During the financial crisis in 2008, Qadan and Yagil (2012) find that ETFs had a low level of tracking ability compared with 2006 and 2007. Furthermore, Chen (2015) concludes the TE of commodity ETFs differs depending on the bullish and bearish conditions in the equity market. In this study, I aim to investigate whether the tracking ability of agricultural ETCs will be affected depending on the alternative market conditions of the underlying agricultural commodity. Accordingly, I examine the difference of the TE of agricultural ETCs between high- and low-volatility periods of the underlying agricultural commodity prices.

2.2.2. Physical versus synthetic replication

Exchange-traded products can adopt two replication methods, either physical replication or synthetic replication. Due to the high cost of storage involved in obtaining commodities via physical replication, the most popular method in commodity investment is synthetic replication. An ETC can synthetically replicate the performance of the benchmark index either using futures contracts or swap contracts. Using futures contracts to replicate adds rolling costs. Hence, there will be a high TE generated for such ETCs. In addition, ETCs using swap contracts may also experience a high level of TE due to the added swap counterparty risk.

This argument related to the impact of replication strategy on the tracking ability of index funds has been studied earlier (Drenovak and Urosevic, 2010; Fassas, 2014; Guedj et al., 2011; Naumenko and Chystiakova, 2015; Rompotis, 2016). According to Guedj et al. (2011) and Rompotis (2016), the tracking deviation of futures-based commodity ETFs is larger compared with physically replicated commodity ETFs. Fassas (2014) and Naumenko and Chystiakova (2015) conclude that ETFs using swap-based replication generate a higher TE compared with physically replicated ETFs. However, the question of whether the replication method affects the tracking ability of agricultural ETCs remains unsolved. Hence, this study aims to add evidence for this research question.

2.2.3. Leveraged versus non-leveraged exchange-traded products

LETCs replicate an underlying index in either a positive or negative multiple and provide a leveraged return on daily basis. ETCs with a positive multiple are known as either bull or leveraged ETCs, whereas ETCs with a negative multiple are known as bear or inverse ETCs (IETCs). These LETCs require daily rebalancing, and this dynamic rebalancing process is likely to make the replication process difficult. Therefore, LETCs are likely to generate a high level of TE compared with traditional ETCs on the same benchmark index. Investors generally consider investing in these products for only short periods in order to avoid these high TEs.

There is a growing number of studies examining the tracking performance of LETFs but limited evidence on LETCs. These studies conclude that the tracking performance of LETFs deteriorates with the investment horizon (Charupat and Miu, 2011; Lu, Wang and Zhang, 2012). However, Lu et al. (2012) find that the US LETFs in their study do not deliver the benchmark return even during a one-week horizon, whereas Charupat and Miu (2011) conclude that Canadian LETFs delivered the promised leveraged benchmark return in a one-week horizon. In the long term, LETFs are reported to underperform the benchmark index (Carver, 2009; Guedj et al., 2011; MacKintosh, 2008; Sullivan, 2009).

2.3. Data

The data sample includes the daily prices of 84 agricultural ETCs (with at least five years of price history) and the daily prices of their underlying agricultural commodity indices. I have collected all this data from the Bloomberg database. The daily prices of ETCs are collected from the inception date of each fund until November 2016. The daily prices of commodity indices cover the period from January 2006 to November 2016.

This sample consists of 50 ETCs issued by the Union Bank of Switzerland (UBS), Switzerland, and 34 ETCs issued by ETFS Commodity Securities Limited, UK. There are 60 funds invested in a single-commodity index and 24 funds invested in a multi-commodities index. Out of these ETCs, 52 funds are primarily traded in the London market and 32 funds are primarily traded in the Swiss market. There are 22 funds leveraged and 62 funds non-leveraged. Fifty funds use futures contracts to replicate the benchmark commodity index and 34 funds use collateralized swap contracts to replicate it. Furthermore, the ETCs in this sample invest in coffee, cotton, corn, cocoa, lean hogs, live cattle, orange juice, rough rice, soybeans, soybean meal, soybean oil, sugar and wheat.

In order to examine the difference in the tracking ability of ETCs during the high- and low-volatility periods of agricultural commodity prices, it is required, firstly, to identify the volatility periods of these commodities. Table 2.1 lists the single-commodity indices used to identify the volatilities of each agricultural commodity in which the ETCs in this study have invested.

[Insert Table 2.1 about here]

In addition, I use the Bloomberg Agriculture Total Return Index (AgriTR Index) as the benchmark to represent the aggregate return on the agricultural market. The AgriTR Index enables investors to gain exposure to a total return investment in a comprehensive basket of agricultural commodity futures contracts on coffee, corn, cotton, soybeans, soybean oil, soybean meal, sugar and wheat. Figure 2.1 displays the composition of the AgriTR Index as at 2 August 2017.

[Insert Figure 2.1 about here]

Thereafter, this study presents the descriptive statistics on ETC returns categorized by the agricultural commodity. Table 2.2 presents the mean returns, volatilities of returns and their distribution by the commodity. ETC returns are calculated using daily ETC prices, and Table 2.2 presents annualized returns and volatilities.

[Insert Table 2.2 about here]

During the period of this analysis, all single-commodity ETCs, except soybean meal, have generated negative annualized mean returns. The lowest mean return is -25.16 percent for wheat and the highest mean return is 13.91 percent for soybean meal. ETCs investing in multi-commodities indices also report a negative mean return of 6.09 percent. The annualized volatility of the daily commodity returns is at the highest (42.51 percent) for corn and at the lowest (20.12 percent) for rough rice. The distribution of ETC returns of cocoa, coffee, corn, rough rice, soybean oil and sugar are negatively skewed, whereas the distribution of ETC returns of cotton, soybeans, soybean meal and wheat are positively skewed.

2.4. Identifying Commodity Price Cycles

To examine the time-varying nature of the tracking performance of agricultural ETCs, first it is required to identify the periods in which commodity prices have experienced significant fluctuations. I adopt two approaches to identify the volatilities in prices. The following sub-sections discuss each method in detail and present the findings of these methods.

2.4.1. Identifying commodity states using the Markov switching regression model

Theoretically, supply-and-demand forces determine commodity prices in the market. Schwartz and Smith (2000) decompose commodity spot prices into short-term deviations and long-term dynamics.[11] This study models the short-term random shocks of commodity returns using the Markov switching (MS) regression model. First, this study assumes that the commodity prices would shift only between two states, that is, high- or low-volatility states. Second, the transition between these states is assumed to follow a Markov process. Finally, it assumes the previous day's return of the benchmark agricultural commodity index (i.e., AgriTR Index) explains today's return of a single-commodity index. In this MS regression model, this study calculates state-dependent intercept terms, slope coefficients and standard deviations using the following model.

$$r_{it} = \mu_{St} + \beta_{St} r_{ag,t-1} + \varepsilon_{St}, \tag{2.1}$$

where r_{it} is the return on commodity index *i* on day *t*, μ_{St} is the state-dependent intercept/ mean, β_{St} is the state-dependent slope coefficient, $r_{ag,t-1}$ is the return of AgriTR Index on day *t-1*, ε_{St} is the state-dependent error term on day t and s_t indicates either state 1 or 2 when *t=1* or *t=2*, respectively. This model estimates the state of each commodity on each day based on the daily transitional probabilities. If the probability of continuing in the same state (i.e., either P11 or P22) is greater than or equals to 0.85, then the commodity is continued in the same state as on the previous date. If the probabilities of P12 or P21 are greater than or equal to 0.85, then

[11] The short-term deviations in prices are temporary changes that arise from unexpected shocks to supply-and-demand forces, whereas long-term dynamics are fundamental changes that arise due to changes in supply-and-demand forces and would continue to persist.

the commodity is considered to have changed the state from 1 to 2 or 2 to 1 compared with the previous date, respectively.

For each single-commodity fund and multi-commodities fund, this study calculates the daily TE from the inception of the fund until November 2016. This study initially calculates the TE using four alternative definitions that will be discussed in a subsequent section. The objective of using different definitions of TE is to ensure the consistency of the findings.

For single-commodity ETCs, I test the significance of the difference in the mean TE of an ETC between state 1 and state 2 of the underlying commodity prices. For multi-commodities funds, I test the significance of the difference in the mean TE of an ETC between the states of each commodity that is included in the fund. For example, consider a multi-commodities fund investing in the Bloomberg Grains Total Return Index, which includes corn, soybeans and wheat. This study examines whether these multi-commodities ETCs show a difference in their tracking ability between the states of each commodity in which the fund invests. I test the significance of the TE difference between the states of corn, soybeans and wheat separately. Accordingly, the null hypothesis is that the difference between the mean TE of state 1 and state 2 is equal to zero, and the alternative hypothesis is that this difference is not equal to zero. If the results reject the null hypothesis, I conclude that TE is different between high- and low-volatility periods. If the results fail to reject the null hypothesis, I conclude that TE is same under both high- and low-volatility periods.

2.4.2. Results of the MS regression model

This section presents the results of the MS regression model (given in equation 2.1 above). Table 2.3 presents the values of the state-dependent intercept (i.e., μ) and the standard deviation of each commodity. Further, it summarizes the average duration (in days) of being in each state and the average transition probabilities between states for each commodity. P11 and P22 represent the probabilities of being in either state 1 or 2 on the previous day and continuing to be in the same state today. P12 and P21 represent the probabilities of being in either state 1 or 2 on the previous day and shifting into state 2 or 1 today, respectively. The higher the probabilities of P11 and P22, the more likely the commodity prices would remain in the same state that they were on the previous day. I also estimate daily transition probabilities (in addition to average probabilities) for each commodity and based on those daily values I identify the state of the commodity on each day.

[Insert Table 2.3 about here]

The results in Table 2.3 show that commodities report a lower mean return in state 1 in comparison with state 2. Except coffee, all other commodities report a standard deviation between 26.19 percent and 49.05 percent during state 1 and a standard deviation between 13.33 percent and 23.81 percent during state 2. The coffee returns show an unusual pattern and report an unexpectedly large standard deviation in state 1. Accordingly, state 1 is the high-volatility period and state 2 is the low-volatility period of agricultural commodity returns. The average duration in state 2 is higher than the average duration in state 1. This reveals that all commodities (except coffee, rough rice and sugar), on average, spend most of the time in state 2, that is, in low-volatility periods.

Finally, I identify the daily state of each commodity based on the daily transitional probabilities of P11 and P22 and consider equal to or above 0.85 as the cut-off level. Figures 2.2 and 2.3 illustrate the daily transitional probabilities (P11 and P22) for cocoa under state 1 and state 2, respectively. It shows that cocoa has mostly been in state 2 during this period of concern as I found for many days P22 of cocoa being greater than 0.85. Accordingly, I could identify the daily states of all commodities except for coffee and orange juice, for which the daily transitional probabilities did not meet the cut-off criteria.

[Insert Figure 2.2 and 2.3 about here]

2.4.3. Identifying abnormal return days of commodities

I use this approach to test the consistency and robustness of the findings with the MS regression model. In their studies, Chen (2015) and Rompotis (2016) examine how the bearish and bullish days in the stock market affect the prices of commodity ETFs. Both these authors identify bearish and bullish days in the stock market by calculating the daily abnormal returns on the equity market.

Following their approach, I identify the days on which each commodity listed in Table 2.1 has significantly outperformed the return on a benchmark agricultural commodity index (i.e., AgriTR Index). The objective of this analysis is to examine whether the tracking performance of agricultural ETCs differs between abnormal return days and normal return days of the underlying commodity. This study uses the following market-adjusted model to calculate the daily abnormal return of a commodity index.

$$AR_{i,t} = r_{i,t} - r_{ag,t}, \tag{2.2}$$

where $AR_{i,t}$ is the abnormal return on a single-commodity index *i* on day *t*, $r_{i,t}$ is the return on single-commodity index *i* on day *t* and $r_{ag,t}$ is the return on the AgriTR Index (multi-commodities index representing the return on total agricultural commodity market) on day *t*. This study tests the null hypothesis that an abnormal return on a single-commodity index *i* on day *t* equals to zero and the alternative hypothesis that an abnormal return on a single-commodity index *i* on day *t* does not equal to zero. The objective of the test is to identify days on which each commodity has reported significant positive or negative abnormal returns.

After identifying significant abnormal return days (both positive and negative), I examine the significance of the tracking difference of each ETC between abnormal return days and normal return days. The null hypothesis of this analysis is that the difference of the mean TE of an ETC between abnormal return days and normal return days is equal to zero. Failure to reject the null hypothesis implies that the TE of ETCs is not the same on both abnormal and normal return days. If the results reject the null hypothesis, it implies that the TE of ETCs are the same under both abnormal and normal return days of the commodity.

For multi-commodities ETCs, my objective is to test whether these funds display a difference in tracking performance between abnormal return and normal return days of each underlying commodity. For example, as mentioned above, consider a multi-commodities fund investing in the Bloomberg Grains Total Return Index, which includes corn, soybeans and wheat. I analyze whether the difference of the mean TE of an ETC is significant between the abnormal and normal return days of each commodity, which is, for corn, soybeans and wheat separately. Failure to reject the null hypothesis implies that multi-commodities ETCs generate a higher TE on abnormal return days of each underlying commodity compared with the normal return days of these commodities.

2.4.4. Results of the abnormal return days of commodities

Table 2.4 summarizes the abnormal return days and normal return days, calculated using equation (2.2) above, for each single-commodity index listed in Table 2.1. The results reveal that, on average, for all the agricultural commodities, there are only 74 and 73 days of significant positive and negative abnormal return days, respectively. This is only a small fraction of the total number of days in the sample period (i.e., 2.75 percent positive abnormal return days and 2.73 percent negative abnormal return days). Soybean meal reports the highest number of positive abnormal return days (i.e., 90 days) and rough rice reports the lowest number of positive abnormal returns days (i.e., 52 days). Lean hogs and orange juice have the largest number of negative abnormal return days (i.e., 85 days) and soybean oil has the lowest number of negative abnormal return days (i.e., 58 days).

[Insert Table 2.4 about here]

2.5. Tracking Performance of Agricultural ETCs

2.5.1. Definitions of TE

Following previous research, this study also calculates daily TEs of ETCs to measure the tracking performance of ETCs. Previous studies used alternative definitions of TE.[12] Following these studies, I also measure the tracking performance of agricultural ETCs using four widely adopted definitions.

First, TE1 is defined as the average of the difference between the fund return on day *t* (r_t^{ETC}) and the underlying index return on day *t* (r_t^I) as shown in equation (2.3) (Drenovak et al., 2014; Rompotis, 2016). The T is the total number of days. TE1 is generally expressed in basis points or (0.01 percent). A positive (negative) TE1 indicates the ETC is over performing (underperforming) compared with the benchmark index.

$$TE_1 = \sum_t^T \frac{r_t^{ETC} - r_t^I}{T} \tag{2.3}$$

Second, TE2 is the average of the absolute value of the difference between the fund return on day *t* and the underlying index return on day *t* or the absolute value of TE1 as shown in equation (2.4) (Charupat and Miu, 2013; Rompotis, 2016). The positive and negative values of TE1 might off-set each other and will not indicate the true magnitude of the TE in that case. Either positive or negative, TE represents a deviation from the promised return. Therefore, TE2 indicates the total of the positive and negative TEs or the absolute value of the TE.

$$TE_2 = \sum_t^T \frac{|r_t^{ETC} - r_t^I|}{T} \tag{2.4}$$

For the third definition, I regress ETC fund returns on the underlying index returns using the model depicted in equation (2.5). TE3 is the standard error of this regression or it is the standard deviation of the residuals (ε_t) of this regression (Charupat and Miu, 2013; Drenovak et al., 2014; Pope and Yadav, 1994; Rompotis, 2008; 2016).

[12] See Charupat and Miu (2013), Drenovak et al. (2014), Frino et al., (2004), Gallagher and Segara (2006), Milonas and Rompotis (2006), Rompotis (2016) and Shin and Soydemir (2010) for different definitions of TE.

$$r_t^{ETC} = \alpha + \beta r_t^I + \varepsilon_t \tag{2.5}$$

Finally, TE4 is defined as the standard deviation of the difference between the fund return and the underlying index return (Charupat and Miu, 2013; Drenovak et al., 2014; Frino and Gallagher, 2001; Roll, 1992; Rompotis, 2016). The formula for calculating the TE4 is given in equation (2.6). TE3 and TE4 measure the co-movement between the fund return and the underlying index return. Further, TE3 and TE4 are both standard deviations and hence, will be expressed as a positive number always. These standard deviations therefore represent the total tracking error (i.e. an aggregate of both negative and positive tracking errors).

$$TE_4 = \sqrt{\frac{1}{T-1}\sum_{t-1}^{T}(r_t^{ETC} - r_t^I)^2} \tag{2.6}$$

Accordingly, I calculate the daily TEs using these four definitions. In all four definitions of TE, if the ETC is precisely replicating the return of the underlying commodity index, the TE should be equals to zero. This study argues that the TE will be different between states and between abnormal and normal return days and tests the significance of the difference in the mean TE. The hypothesis test between MS regression states will be as follows.

$$H0: TE_{S1,J} - TE_{S2,J} = 0 \tag{2.7}$$

$$H1: TE_{S1,J} - TE_{S2,J} \neq 0, \tag{2.8}$$

where $TE_{S1,J}$ is the TE of commodity J in state 1 and $TE_{S2,J}$ is the TE of commodity J in state 2. The hypothesis test between abnormal and normal return days of the underlying commodity will be as follows.

$$H0: TE_{Ab,J} - TE_{N,J} = 0 \tag{2.9}$$

$$H1: TE_{Ab,J} - TE_{N,J} \neq 0, \tag{2.10}$$

where $TE_{Ab,J}$ is the TE of commodity J on abnormal return days and $TE_{N,J}$ is the TE of commodity J on normal return days.

2.5.2. Tracking performance results – Overall sample period

First, this section presents the tracking performance of agricultural ETCs calculated for the entire sample period using the daily price data from the inception of each ETC until November 2016. In this section, I test the null hypothesis that the mean TE of an ETC is equal to zero. Table 2.5 presents the mean TEs calculated under the above four definitions and the respective distribution of each TE. As per TE1, the mean TE is negative for all the commodities. This indicates that agricultural ETCs, on average, underperform the benchmark index, but the results are not statistically significant. The lowest negative TE is reported for soybeans (-0.042 percent), whereas the highest negative TE is reported for wheat (-0.007 percent).

[Insert Table 2.5 about here]

The TEs calculated for the entire sample period using TE2, TE3 and TE4 in Table 2.5 indicate a significant tracking deviation in agricultural ETCs. I find all ETCs to generate significant TEs under all these three definitions. This difference in the results between TE1 and other definitions is possible. Shin and Soydemir (2010) and Rompotis (2016) argue that tracking performance measured as the difference between the fund return and the underlying index return (i.e., TE1) underestimates the error because positive and negative differences in daily returns may cancel out each other. Therefore, I have conducted a sign test[13] to analyze the equality of the signs between fund returns and underlying index returns. The findings of the sign test proved that ETC returns are equally distributed between positive and negative signs. Therefore, I attribute the lack of significant evidence under TE1 to this characteristic of the distribution of ETC returns.

[13] A sign test is a non-parametric test used to investigate whether two variables are equally signed. The null hypothesis is that the median of the differences is zero. I have conducted the sign test to analyse whether fund returns, and underlying index returns have an equal number of positive and negative signs during state 1 and 2 and during abnormal and normal return days. I find that the signs of these returns are equally distributed. I do not present the findings of this test in this thesis, but the results are available upon request.

Furthermore, as mentioned previously, TE3 and TE4 are standard deviations and will be expressed as a positive value. They aggregate both the negative deviations of the TE (underperformance) and the positive deviations of the TE (over performance) into consideration. Hence, TE3 and TE4 demonstrate the aggregate level of TE of a commodity. Theoretically, both underperformance and over performance of an ETC is considered as a deviation from the expected return and therefore, a tracking error. I could observe the same pattern in the results of the TE1 and other definitions in the later results as well. Since the same explanation will be applicable in the later discussion as well, I avoid repeating this explanation.

Finally, I conclude that agricultural ETCs do not effectively replicate the performance of the benchmark index during the overall sample period. The TE of single-commodity ETCs ranges from 1 percent to 2.8 percent, whereas the TE of multi-commodities ETCs is less than 1.5 percent, suggesting that multi-commodities ETCs perform better than single-commodity ETCs. This could be due to the diversification benefits arising from investing in a basket of agricultural commodities rather than investing in a single commodity.

2.5.3. Time-varying tracking performance results

This section aims to investigate the time-varying nature of the tracking performance of agricultural ETCs based on the volatility of agricultural commodity prices. Section 2.4 identified state 1 and state 2 of the commodity prices using the MS regression model. State 1 is the high-volatility period and state 2 is the low-volatility period of agricultural commodity prices. Furthermore, I have identified the abnormal and normal return days of each commodity as well in section 2.4. This study tests whether ETCs show a difference in tracking ability depending on the state of agricultural commodity prices or when the underlying commodity outperforms the overall agricultural commodity market return.

Table 2.6 demonstrates TE and its distribution for single-commodity ETCs. Panel A presents the TE difference between state 1 and state 2, and Panel B presents the TE difference between abnormal and normal return days. For cocoa, soybeans, soybean meal and soybean oil, the TE1 is higher in state 2 (low volatility) than state 1 (high volatility), whereas for all the other commodities TE1 is higher in state 1 than state 2. However, these differences based on TE1 are not statistically significant. According to the results for TE1, there is no significant difference in tracking performance between these alternative volatility periods.

[Insert Table 2.6 about here]

Based on TE2 (i.e., the absolute value of TE1), single-commodity ETCs generate, on average, 1.13 percent higher TE in state 1 than in state 2 and 1.25 percent higher TE during abnormal return days than in normal return days for all the commodities. The results on TE3 and TE4 also support the fact that the TE of single-commodity ETCs is significantly higher in high-volatility periods and on abnormal return days. In summary, based on TE2, TE3 and TE4, I conclude that tracking performance of single-commodity ETCs varies depending on the volatility of the underlying commodity prices.

Table 2.7 displays the tracking performance of multi-commodities ETCs and their distributions. This study tests whether multi-commodities ETCs perform differently when at least one commodity in which they have invested experiences periods of high volatility or abnormal returns. In this table as well, Panel A presents the TE difference under state 1 and state 2, and Panel B presents the TE difference under abnormal and normal return days.

[Insert Table 2.7 about here]

In the case of multi-commodities ETCs with TE1, there are only three and four ETCs (out of 24 multi-commodities ETCs) reporting both positive and negative significant tracking deviations between states and between abnormal and normal returns days, respectively. Under the other three definitions, a majority of multi-commodities ETCs report positive and significant TE differences during the price cycle of each commodity. According to TE2, on average, the difference in daily TE of multi-commodities funds is 0.46 percent between state 1 and state 2 and 0.35 percent between abnormal and normal return days. This indicates that multi-commodities ETCs are unable to better track the benchmark commodity index during high-volatility periods of agricultural commodity prices compared with low-volatility periods. The TE differences calculated based on TE3 and TE4 also confirm the fact that the volatility of TEs is higher in state 1 than in state 2 and higher in abnormal return days than normal return days.

There is another noteworthy fact revealed in the reported results. By comparing the tracking error values presented in Table 2.6 and Table 2.7, I identified that the TE values of multi-commodities ETCs are lower than those of single-commodity ETCs. This indicates that multi-commodities ETCs show a better ability in tracking the underlying index during high-volatility periods than single-commodity ETCs. A possible explanation for this improved tracking performance of multi-commodities ETCs could be the diversification effect.

2.5.4. Tracking performance difference based on replication strategy

The next aim is to investigate the tracking performance difference in ETCs depending on the replication method adopted. A priori, I expect synthetically replicated ETCs to produce a higher level of TE compared with physically replicated ETCs.

In the selected sample of ETCs, there are only three exactly matching pairs of ETCs tracking the same underlying index, trading on the same exchange and denominated in the same currency, but one ETC is replicated physically, whereas the other is replicated synthetically. Given this limitation in the matching pairs, I follow the methodology of Rompotis (2016), who examines this tracking performance difference by calculating the mean TE values of all the ETCs replicated either physically or synthetically. He does not compare the tracking performance difference using exactly matching pairs of ETCs.

Accordingly, I have single-commodity ETCs and multi-commodities ETCs replicated using futures contracts or swaps. These ETCs invest in the same underlying commodity but are not traded in the same exchange. I categorize these ETCs by commodity and then by the replication strategy. Then, I calculate the difference of the mean TE of the categorized ETCs using the four TE definitions mentioned above.

Table 2.8 presents the mean TE values of ETCs based on the replication strategy. These TEs are calculated for the entire sample period, high- and low-volatility period separately. As I could not identify the states for coffee in Section 4, I could not calculate the TE for coffee under alternative market states. According to my results, single-commodity ETCs replicated using swap contracts produce a higher level of TE than single-commodity ETCs replicated using futures contracts (except in the case of TE1) during the examined period. Furthermore, the TE is higher under the high-volatility period than the low-volatility period of agricultural commodity prices under both replication strategies.

[Insert Table 2.8 about here]

Thereafter, Table 2.9 summarizes the tracking performance of multi-commodities ETCs based on the replication strategy under state 1 and state 2 of each underlying commodity in which they have invested. This study examines whether multi-commodities ETCs also display a tracking performance difference based on the replication strategy under each state. The results presented in Table 2.9 support the above two findings. First, multi-commodities ETCs replicated using swap contracts report higher TEs than multi-commodities ETCs replicated using futures contracts. Second, both replication strategies generate a higher level of TE in state 1 than in state 2.

[Insert Table 2.9 about here]

Accordingly, the findings of this study conclude that synthetic replication is not a better method of tracking the benchmark index. In particular, agricultural ETCs replicated using swap contracts display inefficient tracking abilities than agricultural ETCs replicated using futures contracts. Furthermore, the results suggest that both synthetic replication strategies generate a higher TE during the high-volatility periods than low-volatility periods of the underlying commodity.

2.5.5. Tracking performance difference based on leverage

This section examines the difference in the tracking performance of ETCs based on the level of leverage of an ETC. There are nine trios of ETCs investing in the same agricultural commodity index. The trio includes a traditional ETC, a leveraged ETC and an inverse ETC investing in the same agricultural commodity index. Theoretically, I expect LETCs and IETCs to produce a higher TE due to the daily rebalancing required to maintain the leverage. Therefore, this study tests the alternative hypothesis that the TE of a LETC/IETC is higher than the TE of a traditional ETC during the period of concern in this study. The null hypothesis is that the TE of an LETC/IETC is lower or greater than that of a traditional ETC.

Table 2.10 presents the results of this analysis. Under LETCs, the results consistently reject the null hypothesis with TE2, TE3 and TE4. Under IETCs, the results consistently reject the null hypothesis with TE2 and TE4 (whereas the findings with TE3 are mixed). TE2 measures the absolute deviation of the TE whereas TE3 and TE4 measures the variability of TE. With this evidence, I support the alternative hypothesis that leverage increases the TE of an agricultural ETC compared with the TE of a traditional ETC. In conclusion, this study adds supportive evidence for the argument that leverage increases the level of TE.

[Insert Table 2.10 about here]

2.6. Persistence of TE

2.6.1. Measuring the persistence of TE

The previous Section 2.5 presented evidence for the existence of significant TE for agricultural ETCs during the sample period. The results also suggest that TE is time varying depending on the volatility periods of agricultural commodities. Finally, I investigate the persistence of this

TE in the short run. The hypothesis of persistence assumes that the TE of the previous two days will continue and will have an impact on the TE of today as well.

Previous studies have adopted different methods to test the persistence of TE. Shin and Soydemir (2010) employ a serial correlation test to assess the persistence of TE. They find significant serial correlation coefficients, on average, up to six days in Asian markets, up to five days in European markets and only one day in US markets. Rompotis (2016) uses an autoregressive model to test the persistence, and finds negative coefficients which conclude that the TE of commodity ETFs has a mean-reverting behaviour.

This study follows Rompotis (2016) and adopts the following autoregressive model to test the persistence of TE in agricultural ETCs. I test the persistence using the absolute value definition (i.e., TE2) to avoid underestimating the TE that would occur if I use the TE1 definition. The model for testing persistence of TE is as follows.

$$TE2_{i,t} = \alpha_i + \beta_{1,i} TE2_{i,t-1} + \beta_{2,i} TE2_{i,t-2} + \varepsilon_{i,t}, \tag{2.11}$$

where $TE2_{i,t}$, $TE2_{i,t-1}$ and $TE2_{i,t-2}$ are TEs of ETC i on day t, on day *t-1* and on day *t-2*, respectively. This model assumes that the TE today depends on the previous two days' TE, that is, on days *t-1* and *t-2*. The error variance of this regression is modelled with a generalized autoregressive conditional heteroscedasticity model, that is, GARCH (1,1) process.

The persistence of the TE is determined based on the significance of the β coefficients. TE is persistent if at least one β coefficient is positive and significant. This implies that if an ETC has shown either under- or over-exposure to the benchmark index in the previous two days, it will continue to today as well. Negative and significant β coefficients show a mean-reverting behavior of TE. If β coefficients are not significant, it suggests that TE is not persistent. If α_i terms are significant, it reflects a proportion of TE that cannot be explained by the lagged values of the TE. Hence, this analysis tests the significance of $\alpha_i, \beta_{1,i}$ and $\beta_{2,i}$ separately.

2.6.2. Results of the persistence of TE

Table 2.11 presents the results of the persistence test of TEs. This table summarizes α_i, $\beta_{1,i}$ and $\beta_{2,i}$ coefficients and their distributions, respectively. According to the results, there are only 15 ETCs (out of 84 funds) in the sample reporting a positive and significant $\beta_{1,i}$ coefficient and only 9 ETCs reporting a positive and significant $\beta_{2,i}$ coefficient. There are no sufficient results to conclude that today's TE is independent of the past two days TE. I find only one ETC reporting negative and significant $\beta_{1,i}$ and $\beta_{2,i}$ coefficients and this reflects a mean-reverting behaviour in TE. For all 84 funds, I find positive and significant α_i coefficients. In conclusion, though agricultural ETCs report a significant level of TE, there is no strong evidence for its persistence. Furthermore, there is a significant portion of TE that is not explained by the past two days' TE of an agricultural ETC.

[Insert Table 2.11 about here]

2.7. Conclusion

This study aims to add evidence on the tracking performance of European agricultural ETCs. I investigate whether the TE is time varying depending on the high- and low-volatility periods in the underlying agricultural commodity prices. Then, I examine whether the tracking performance varies depending on the characteristics of the structure of ETC. Finally, I study whether the TE is persistent in the short term.

The results show that agricultural ETCs do not replicate the benchmark index accurately during the period of concern. In particular, I find these ETCs produce a high level of TE when agricultural commodity prices are highly volatile. Furthermore, the results reveal that single-commodity ETCs, on average, generate more TE than multi-commodities ETCs. At the same time, I do not find strong evidence for the persistence of this significant TE. Finally, the results confirm the fact that fund characteristics, such as replication strategy and the level of leverage, affect the tracking ability of ETCs significantly.

The implications of this study are important for both issuers and investors. Since this study provides evidence that the structure of an ETC matters for its tracking ability, issuers must consider this fact when designing new ETCs on agricultural commodities. In addition, issuers need to pay attention to the finding that single-commodity ETCs have a poor tracking ability compared with multi-commodities ETCs during high-volatility periods compared with low-volatility periods. The quality of an ETC depends on the ability to provide the promised benchmark return for investors. Therefore, issuers of these ETCs have a responsibility to design ETCs with the best possible structure to avoid this limitation.

Conversely, investors should pay attention to these findings, as these ETCs expose investors to a high level of time-varying TE. However, the lack of persistence in TE shows that there is no systematic problem in how ETCs operate. This study supports the argument that fund characteristics, such as replication strategy and leverage, affect the level of tracking performance.

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Appendix 1

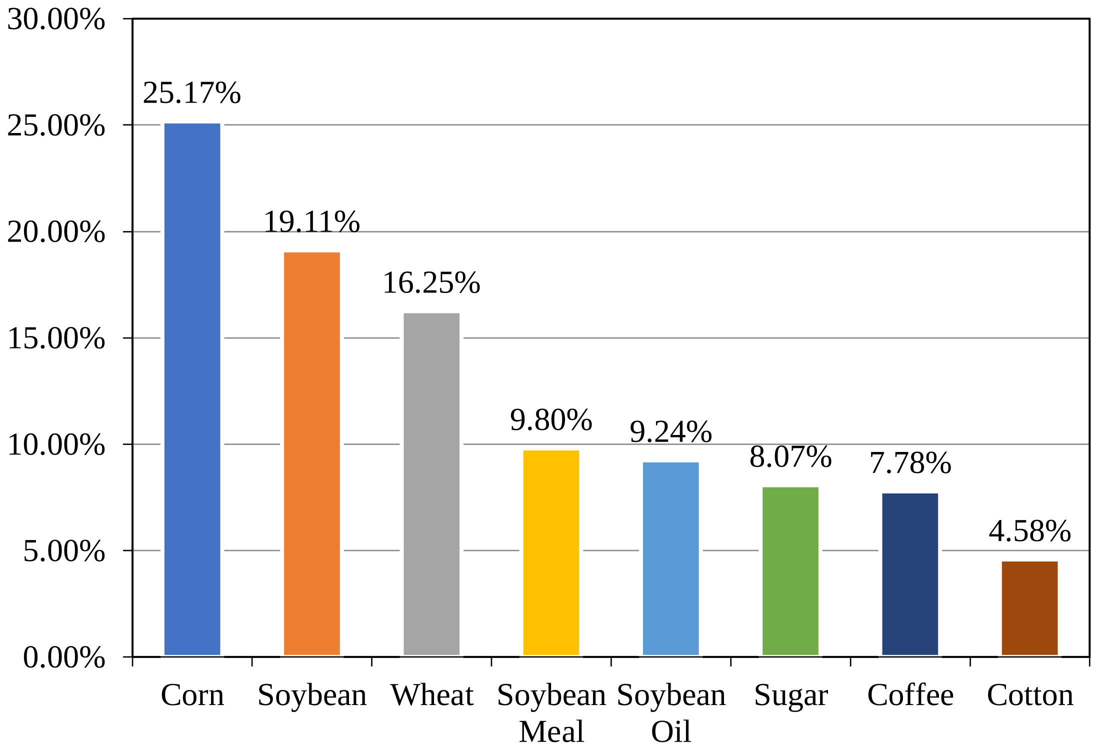

Figure 2.1: Composition of AgriTR Index
Source: Bloomberg (As at 2 August 2017)

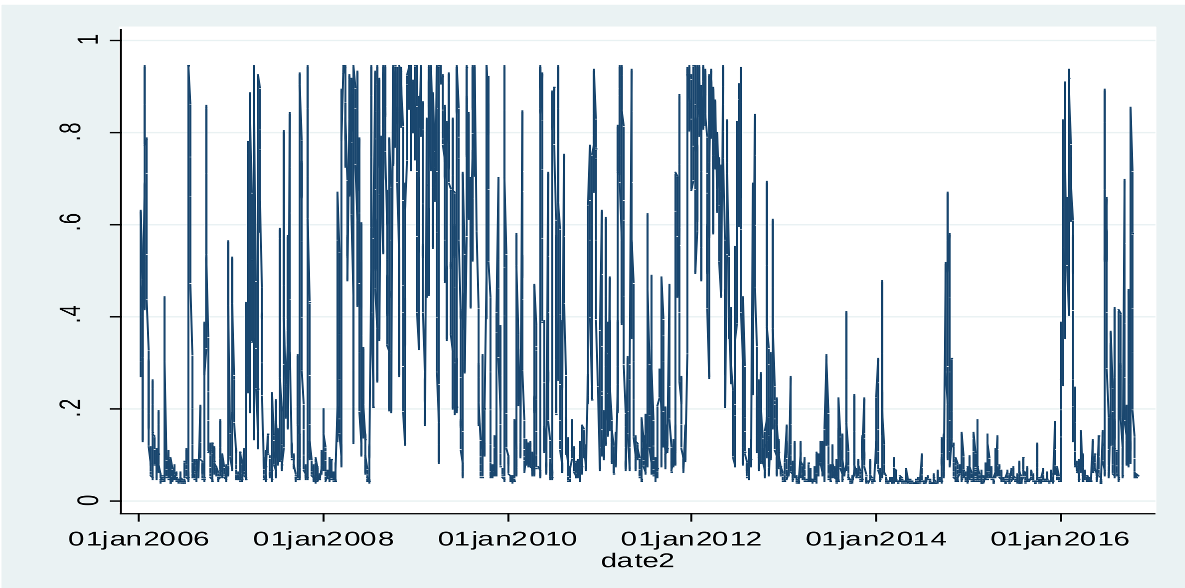

Figure 2.2: Daily Transitional Probabilities of Cocoa for State 1
Source: Authors' work

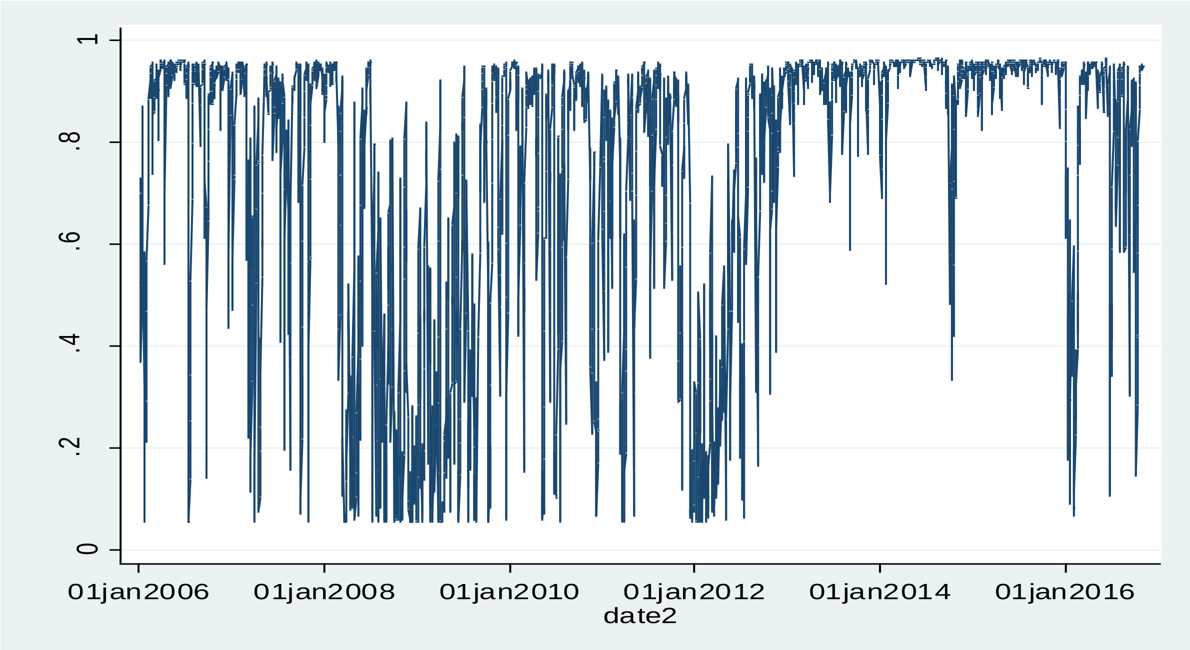

Figure 2.3: Daily Transitional Probabilities of Cocoa for State 2
Source: Authors' work

Appendix 2

Table 2.1: List of commodities and their respective indices

This table lists the agricultural commodities and their respective commodity index in which the sample of 84 ETCs in this study has invested. The historical daily price data for all these indices are obtained from the Bloomberg database for the period from January 2006 to November 2016.

Commodity	Index	Index Ticker
Cocoa	Bloomberg Cocoa Sub Index Total Return	BCOMCCTR
Coffee	Bloomberg Coffee Sub Index Total Return	BCOMKCTR
Corn	Bloomberg Corn Sub Index Total Return	BCOMCNTR
Cotton	Bloomberg Cotton Sub Index Total Return	BCOMCTTR
Lean Hogs	Bloomberg Lean Hogs Total Return Index	BCOMLHTR
Live Cattle	Bloomberg Live Cattle Total Return Index	BCOMLCTR
Orange Juice	Bloomberg Orange Juice Sub Index Total Return	BCOMOJT
Rough Rice	UBS Bloomberg CMCI Rough Rice Total Return Index	CTRRTR
Soybeans	Bloomberg Soybeans Sub Index Total Return	BCOMSYTR
Soybean Meal	Bloomberg Soybean Meal Sub Index Total Return	BCOMSMT
Soybean Oil	Bloomberg Soybean Oil Sub Index Total Return	BCOMBOTR
Sugar	Bloomberg Sugar Sub Index Total Return	BCOMSBTR
Wheat	Bloomberg Wheat Sub Index Total Return	BCOMWHTR

Table 2.2: Descriptive statistics

This table reports descriptive statistics of the 84 funds in the sample. The single-commodity ETCs are categorized based on their underlying commodity and multi-commodities ETCs are reported separately. The data covers the period from the inception of a fund until November 2016. The table summarizes the number of funds under each commodity category and the number of observations (No of Obs). All mean returns and standard deviations (SD) of fund returns are annualized. The last column reports the skewness of the return distribution.

Commodity	No of Funds	No of Obs	Mean Return	SD of Return	Skewness
Cocoa	9	14532	-6.89%	30.30%	-43.16%
Coffee	6	10499	-19.49%	40.91%	-58.57%
Corn	8	13306	-12.59%	42.51%	-88.24%
Cotton	6	10431	-8.61%	39.26%	17.24%
Rough Rice	3	2882	-24.25%	18.55%	-12.03%
Soybeans	5	7980	-11.09%	37.73%	46.48%
Soybean Meal	1	1085	13.91%	26.16%	1.22%
Soybean Oil	4	7906	-13.12%	32.59%	-26.78%
Sugar	9	15411	-7.95%	38.53%	-16.19%
Wheat	9	15820	-25.16%	42.25%	15.89%
Multi- Commodities	24	45967	-6.09%	28.88%	-81.14%

Table 2.3: Markov switching regression results

This table summarizes the results of the Markov switching regression model for state 1 and state 2. It reports the state-dependent mean return and the standard deviation. These mean returns and standard deviation values are calculated using daily data and then annualized. State 1 is the high-volatility period and state 2 is the low-volatility period of each commodity. This table also provides the average duration of each commodity being in each state and average transition probabilities. P11 and P22 represent the probabilities of being in state 1 or 2 on the previous day and continuing to be in the same state today. P12 and P21 represent the probabilities of being on either state 1 or 2 on the previous day and shifting into either state 2 or 1, respectively, today.

Commodity & Index	State 1			State 2			Transition Probabilities			
	Mean Return	Standard Deviation	Duration (Days)	Mean Return	Standard Deviation	Duration (Days)	P11	P12	P22	P21
Cocoa (BCOMCCTR)	-39.61%	40.96%	19	28.65%	20.32%	50	0.946	0.054	0.98	0.02
Coffee (BCOMKCTR)	-13.41%	395.59%	2	-6.95%	17.94%	2	0.5537	0.4463	0.5405	0.4595
Corn (BCOMCNTR)	-19.43%	41.91%	18	7.46%	20.95%	31	0.9458	0.0542	0.968	0.032
Cotton (BCOMCTTR)	-13.41%	39.37%	88	3.67%	19.84%	239	0.9889	0.0111	0.9958	0.0042
Lean Hogs (BCOMLHTR)	-49.57%	32.70%	42	-6.95%	19.37%	129	0.9762	0.0238	0.9922	0.0078
Live Cattle (BCOMLCTR)	-69.58%	53.97%	37	11.40%	23.97%	88	0.9731	0.0269	0.9887	0.0113
Orange Juice (BCOMOJT)	-37.39%	49.05%	3	28.65%	20.32%	7	0.71	0.29	0.8596	0.1404
Rough Rice (CTRRTR)	-16.48%	26.19%	49	3.67%	13.33%	31	0.9795	0.0205	0.9679	0.0321
Soybean Meal (BCOMSMT)	33.36%	38.73%	28	15.49%	20.80%	59	0.9637	0.0363	0.9829	0.0171
Soybean Oil (BCOMBOTR)	-35.10%	38.26%	106	3.67%	19.68%	596	0.9905	0.0095	0.9983	0.0017
Soybeans (BCOMSYTR)	-10.24%	36.51%	26	19.72%	17.62%	65	0.962	0.038	0.9847	0.0153
Sugar (BCOMSBTR)	43.31%	41.27%	87	-37.39%	22.07%	83	0.9886	0.0114	0.9879	0.0121
Wheat (BCOMWHTR)	38.24%	43.02%	40	-37.39%	23.81%	54	0.9751	0.0249	0.9814	0.0186

Table 2.4: Abnormal and normal return days of commodities

Abnormal return is the difference between the return of each commodity index and the Bloomberg Agriculture Total Return (AgriTR) Index return. This table presents the number of days each commodity has reported either a significant positive or negative abnormal return or no significant abnormal return. Positive (negative) percentage is the positive (negative) abnormal return days as a percentage of the total number of days in the sample period.

Commodity & Index	Significant Abnormal Return Days				Normal Returns Days
	Positive (Days)	Positive (Percentage)	Negative (Days)	Negative (Percentage)	
Cocoa (BCOMCCTR)	64	2.38%	78	2.90%	2546
Coffee (BCOMKCTR)	76	2.83%	75	2.79%	2537
Corn (BCOMCNTR)	67	2.49%	71	2.64%	2550
Cotton (BCOMCTTR)	70	2.60%	76	2.83%	2542
Lean Hogs (BCOMLHTR)	81	3.01%	85	3.16%	2525
Live Cattle (BCOMLCTR)	78	2.90%	76	2.82%	2537
Orange Juice (BCOMOJT)	80	2.97%	85	3.16%	2528
Rough Rice (CTRRTR)	52	1.96%	64	2.41%	2542
Soybean Meal (BCOMSMT)	90	3.35%	70	2.60%	2528
Soybean Oil (BCOMBOTR)	88	3.27%	58	2.16%	2542
Soybeans (BCOMSYTR)	78	2.90%	60	2.23%	2550
Sugar (BCOMSBTR)	66	2.46%	76	2.83%	2546
Wheat (BCOMWHTR)	71	2.64%	80	2.98%	2537

Table 2.5: Tracking performance of ETCs – Entire sample period

This table reports average daily TEs measured using the four definitions and the distribution of TE. The single-commodity funds are categorized based on their underlying commodity and the 24 multi-commodities ETCs are reported separately. The data covers the period from the inception of a fund until November 2016. The second column reports the number of funds in each commodity. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: TE3 defines TE as the standard error of a regression of ETC return on the underlying index return: TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. Distribution column reports the distribution of each TE as follows: the number of positive and significant funds (+)/ the number of insignificant funds (0)/ and the number of negative and significant funds (-). The significance of the TE is determined at the 5% significance level.

Commodity	No of Funds	TE1	Distribution of TE1 +/0/-	TE2	Distribution of TE2 +/0/-	TE3	Distribution of TE3 +/0/-	TE4	Distribution of TE4 +/0/-
Cocoa	9	-0.010%	0/9/0	0.941%	9/0/0	0.922%	9/0/0	1.393%	9/0/0
Coffee	6	-0.020%	0/6/0	1.670%	6/0/0	0.844%	6/0/0	2.396%	6/0/0
Corn	8	-0.017%	0/8/0	1.513%	8/0/0	1.922%	8/0/0	2.519%	8/0/0
Cotton	6	-0.036%	0/6/0	1.509%	6/0/0	1.755%	6/0/0	2.818%	6/0/0
Rough Rice	3	-0.009%	0/3/0	0.934%	3/0/0	1.050%	3/0/0	1.326%	3/0/0
Soybeans	5	-0.042%	0/5/0	1.298%	5/0/0	1.450%	5/0/0	1.921%	5/0/0
Soybean Meal	1	-0.013%	0/1/0	1.124%	1/0/0	1.323%	1/0/0	1.560%	1/0/0
Soybean Oil	4	-0.012%	0/4/0	1.358%	4/0/0	1.388%	4/0/0	1.923%	4/0/0
Sugar	9	-0.010%	0/9/0	1.319%	9/0/0	1.591%	9/0/0	2.158%	9/0/0
Wheat	9	-0.007%	0/9/0	1.552%	9/0/0	1.885%	9/0/0	2.343%	9/0/0
Multi- Commodities	24	-0.013%	0/24/0	0.998%	24/0/0	1.125%	24/0/0	1.479%	24/0/0

Table 2.6: Time-varying tracking performance of single-commodity ETCs

This table summarizes the difference between the TE and the distribution of TE of single-commodity funds. The data covers the period from the inception of a fund until November 2016. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: TE3 defines TE as the standard error of a regression of ETC return on the underlying index return: TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. Distribution column reports the distribution of each TE as follows: the number of positive and significant funds (+)/ the number of insignificant funds (0)/ and the number of negative and significant funds (-). Panel A summarizes the results between state 1 and state 2. Panel B summarizes the results between abnormal return days and normal return days. The significance of the TE is determined at the 5% significance level.

Panel A – State 1 (High-volatility) versus State 2 (Low-volatility)

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	-0.07%	0/9/0	0.61%	9/0/0	1.8221	9/0/0	1.6444	9/0/0
Corn	0.02%	0/8/0	1.77%	8/0/0	3.3455	8/0/0	2.5061	8/0/0
Cotton	0.03%	0/6/0	1.22%	6/0/0	2.3865	6/0/0	1.8675	6/0/0
Rough Rice	0.01%	0/3/0	0.62%	3/0/0	2.6407	3/0/0	1.8663	3/0/0
Soybeans	-0.12%	0/5/0	1.40%	5/0/0	2.8853	5/0/0	2.5546	5/0/0
Soybean Meal	-0.03%	0/1/0	1.08%	1/0/0	2.8835	1/0/0	2.3243	1/0/0
Soybean Oil	-0.02%	0/4/0	1.18%	4/0/0	2.3289	4/0/0	2.3479	4/0/0
Sugar	0.01%	0/9/0	1.04%	9/0/0	2.5373	9/0/0	2.5361	9/0/0
Wheat	0.02%	0/9/0	1.26%	9/0/0	2.5339	9/0/0	2.2165	9/0/0

Panel B – Abnormal Return Days versus Normal Return Days

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	0.14%	1/8/0	1.07%	9/0/0	1.5963	9/0/0	1.8203	8/1/0
Coffee	0.27%	0/6/0	1.86%	6/0/0	1.6949	6/0/0	1.9576	6/0/0
Corn	-0.23%	0/8/0	1.61%	8/0/0	1.6747	8/0/0	1.6492	8/0/0
Cotton	0.58%	1/5/0	1.53%	5/1/0	1.7130	6/0/0	1.3823	5/0/1
Rough Rice	0.26%	0/3/0	0.19%	0/3/0	0.8571	0/3/0	1.1961	0/3/0
Soybeans	0.23%	0/5/0	1.01%	5/0/0	1.3361	4/1/0	1.5642	4/1/0
Soybean Meal	0.49%	0/1/0	1.18%	1/0/0	1.5277	1/0/0	1.8389	1/0/0
Soybean Oil	0.33%	1/3/0	0.94%	4/0/0	1.2815	3/1/0	1.4687	3/1/0
Sugar	-0.44%	0/8/1	1.32%	9/0/0	1.4740	8/1/0	1.5814	8/0/1
Wheat	-0.48%	0/9/0	1.79%	9/0/0	1.6966	9/0/0	1.8757	9/0/0

Table 2.7: Time-varying tracking performance of the multi-commodities ETCs

This table summarizes the difference between the TE and the distribution of TE of single-commodity funds. The data covers the period from the inception of a fund until November 2016. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: TE3 defines TE as the standard error of a regression of ETC return on the underlying index return: TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. Distribution column reports the distribution of each TE as follows: the number of positive and significant funds (+)/ the number of insignificant funds (0)/ and the number of negative and significant funds (-). Panel A summarizes the results between state 1 and 2. Panel B summarizes the results between abnormal return days and normal return days. The significance of the TE is determined at the 5% significance level.

Panel A – State 1 (High-volatility) versus State 2 (Low-volatility)

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	0.07%	0/12/0	0.17%	5/6/0	1.3451	5/5/1	0.9823	11/0/0
Corn	-0.05%	0/20/0	0.88%	20/0/0	2.8556	20/0/0	2.1900	20/0/0
Cotton	-0.01%	0/15/0	0.56%	14/0/0	1.7709	14/0/0	1.6804	14/0/0
Lean Hogs	0.01%	0/6/0	0.04%	0/6/0	1.2119	3/3/0	1.1801	5/1/0
Live Cattle	-0.06%	0/6/0	0.09%	2/4/0	1.3019	6/0/0	1.2917	6/0/0
Soybeans	-0.06%	0/20/0	0.74%	20/0/0	2.0879	20/0/0	1.8672	20/0/0
Soybean Meal	-0.05%	0/16/0	0.57%	16/0/0	2.0500	16/0/0	1.7346	16/0/0
Soybean Oil	-0.05%	0/16/0	0.57%	11/5/0	1.8008	16/0/0	1.5891	16/0/0
Sugar	0.02%	1/17/2	0.41%	20/0/0	1.6357	20/0/0	1.4214	16/4/0
Wheat	0.01%	0/20/0	0.62%	20/0/0	1.9536	20/0/0	1.7896	20/0/0

Panel B – Abnormal Return Days versus Normal Return Days

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	0.24%	1/11/0	0.37%	6/6/0	1.3819	11/1/0	1.4146	11/1/0
Coffee	0.00%	0/20/0	0.20%	3/17/0	1.0381	3/16/1	1.1306	15/4/1
Corn	0.13%	0/20/0	0.58%	18/2/0	1.4290	19/1/0	1.4419	18/2/0
Cotton	0.05%	0/15/0	0.33%	13/2/0	1.2447	13/1/1	1.2546	12/2/1
Lean Hogs	-0.13%	0/6/0	0.29%	4/2/0	1.4195	6/0/0	1.4796	6/0/0
Live Cattle	-0.04%	0/6/0	0.41%	6/0/0	1.6631	6/0/0	1.5094	6/0/0
Orange Juice	0.03%	0/3/0	0.27%	2/1/0	1.1981	2/1/0	1.1065	1/2/0
Soybeans	-0.04%	0/20/0	0.38%	19/1/0	1.2385	18/2/0	1.2155	14/6/0
Soybean Meal	0.04%	0/16/0	0.36%	16/0/0	1.3357	15/1/0	1.2775	13/4/0
Soybean Oil	0.12%	3/13/0	0.18%	3/13/0	1.1442	7/9/0	1.1570	8/8/0
Sugar	-0.08%	0/20/0	0.32%	10/10/0	1.2000	13/6/1	1.2197	11/8/1
Wheat	-0.20%	0/20/0	0.55%	20/0/0	1.4125	19/1/0	1.4206	18/2/0

Table 2.8: Tracking performance based on replication strategy of single-commodity ETCs

This table presents the mean TE values of each commodity based on the replication strategy of the ETC for the overall period, under the high-volatility period and low-volatility period. The ETCs selected in this study are either replicated using futures contracts or fully funded collateralized swaps. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: TE3 defines TE as the standard error of a regression of ETC return on the underlying index return: TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. The data covers the period from the inception of a fund until November 2016.

Commodity	Replication Strategy	No of Funds	Overall Period				State 1 (High-Volatility)				State 2 (Low-Volatility)			
			TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4
Cocoa	Futures	6	-0.0020%	0.6776%	0.9115%	1.0699%	-0.0892%	1.0959%	1.3227%	1.3929%	-0.0158%	0.5595%	0.7111%	0.8592%
Cocoa	Swap	3	-0.0215%	1.4678%	0.9427%	2.0405%	-0.0787%	1.9823%	1.2734%	2.6086%	-0.0092%	1.2371%	0.7431%	1.6489%
Coffee	Futures	3	-0.0198%	1.3826%	1.2181%	2.0220%	-	-	-	-	-	-	-	-
Coffee	Swap	3	-0.0195%	1.9584%	0.4698%	2.7705%	-	-	-	-	-	-	-	-
Corn	Futures	6	-0.0075%	1.2106%	1.5171%	1.9771%	0.0553%	2.2084%	2.6943%	2.9118%	-0.0290%	0.8801%	1.0314%	1.5321%
Corn	Swap	2	-0.0471%	2.4217%	3.1369%	4.1456%	-0.1706%	4.8022%	7.3164%	8.7433%	-0.0068%	1.7226%	1.5078%	2.3112%
Cotton	Futures	3	-0.0289%	1.1631%	1.3404%	2.8036%	0.0131%	1.8012%	2.3481%	2.4998%	-0.0975%	0.9354%	0.8934%	2.4888%
Cotton	Swap	3	-0.0421%	1.8550%	2.1691%	2.8327%	-0.0720%	2.9648%	3.3086%	4.2628%	-0.0212%	1.3947%	1.5306%	2.0039%
Soybeans	Futures	3	-0.0341%	0.9020%	1.1080%	1.3163%	-0.1973%	1.8090%	2.1312%	2.3224%	-0.0047%	0.6383%	0.6889%	0.9017%
Soybean	Swap	2	-0.0547%	1.8930%	1.9633%	2.8285%	-0.0447%	3.1824%	3.4125%	4.6982%	-0.0298%	1.4451%	1.2505%	1.8978%
Soybean Oil	Futures	1	-0.0191%	0.9172%	1.0761%	1.2519%	-0.0415%	1.6051%	1.7981%	2.0324%	-0.0139%	0.7368%	0.7979%	0.9632%
Soybean Oil	Swap	3	-0.0093%	1.5043%	1.4924%	2.1466%	-0.0268%	2.5872%	2.6720%	3.7439%	-0.0043%	1.3020%	1.1360%	1.6670%
Sugar	Futures	6	0.0039%	0.9586%	1.4283%	1.8201%	0.0231%	1.4939%	2.0695%	2.2141%	-0.0282%	0.5871%	0.7418%	0.8472%
Sugar	Swap	3	-0.0391%	2.0389%	1.9165%	2.8339%	-0.0621%	2.6644%	2.4674%	3.5485%	0.0067%	1.3462%	0.9902%	1.7752%
Wheat	Futures	6	-0.0058%	1.2445%	1.6068%	1.8748%	-0.0143%	2.0021%	2.5480%	2.7912%	-0.0386%	0.9216%	1.1214%	1.3734%
Wheat	Swap	3	-0.0104%	2.1667%	2.4421%	3.2788%	0.0164%	3.2150%	4.1422%	5.2029%	0.0064%	1.5984%	1.4038%	2.0734%
Multi- Commodities	Futures	12	-0.0059%	0.7185%	0.9254%	1.1341%	-	-	-	-	-	-	-	-
Multi- Commodities	Swap	12	-0.0194%	1.2768%	1.3249%	1.8233%	-	-	-	-	-	-	-	-

Table 2.9: Tracking performance based on the replication strategy of multi-commodities ETCs

This table presents the mean TE values of multi-commodities ETCs categorized based on both the underlying commodity and the replication strategy of the ETC under the high- and low-volatility periods. The ETCs selected in this study are either replicated using futures contracts or fully funded collateralized swaps. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: TE3 defines TE as the standard error of a regression of ETC return on the underlying index return: TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. The data covers the period from the inception of a fund until November 2016.

Commodity	Replication Strategy	Number of Funds	State 1 (High-Volatility)				State 2 (Low-Volatility)			
			TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4
Corn	Futures	12	-0.0380%	1.2518%	1.5746%	1.7167%	-0.0237%	0.5401%	0.6414%	0.8252%
Corn	Swap	8	-0.1192%	2.1071%	2.3767%	3.0435%	-0.0067%	0.9665%	0.9117%	1.2942%
Cotton	Futures	6	0.0023%	1.1050%	1.3789%	1.4880%	-0.0144%	0.6179%	0.7472%	0.9584%
Cotton	Swap	8	-0.0420%	1.6196%	1.6307%	2.3312%	-0.0038%	1.0031%	0.9539%	1.3424%
Soybeans	Futures	12	-0.0751%	1.1610%	1.4770%	1.5651%	-0.0135%	0.5809%	0.7200%	0.8778%
Soybeans	Swap	8	-0.0535%	2.0334%	2.1568%	2.8165%	-0.0082%	1.0451%	1.0229%	1.4113%
Soybean Meal	Futures	12	-0.0764%	1.0903%	1.3833%	1.4810%	-0.0190%	0.5876%	0.7336%	0.8790%
Soybean Meal	Swap	4	-0.0211%	1.7124%	1.6719%	2.3158%	-0.0031%	0.9477%	0.9228%	1.2832%
Soybean Oil	Futures	12	-0.0741%	1.1282%	1.4309%	1.5170%	-0.0238%	0.6462%	0.8112%	1.0049%
Soybean Oil	Swap	4	-0.0650%	1.8392%	1.7711%	2.5380%	-0.0088%	1.0206%	1.0183%	1.3866%
Sugar	Futures	12	0.0009%	0.9263%	1.1600%	1.2707%	-0.0612%	0.5893%	0.6953%	1.0123%
Sugar	Swap	8	-0.0250%	1.4468%	1.4412%	2.0261%	0.0062%	0.9301%	0.8909%	1.2525%
Wheat	Futures	12	-0.0247%	1.0484%	1.3526%	1.5644%	-0.0327%	0.5622%	0.6864%	0.8906%
Wheat	Swap	8	0.0084%	1.7944%	1.8786%	2.5166%	-0.0057%	0.9847%	0.9738%	1.3292%

Table 2.10: Tracking performance difference based on leverage

This table shows the results of the null hypothesis test that the TE of a LETC/IETC is lower than the TE of a traditional ETC tracking the same underlying commodity index. The alternative hypothesis is that the TE of a LETC/IETC is higher than the TE of a traditional ETC. There are 9 trios of ETCs replicating the same index. There are 6 single commodity ETCs and 3 multi-commodities ETCs. The data covers the period from the inception of each fund until November 2016. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: TE3 defines TE as the standard error of a regression of ETC return on the underlying index return: TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. The table reports p values of the test and * reports the significance at the 5% level.

Commodity	Index	No of observations	Leverage versus Traditional				Inverse versus Traditional			
			TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4
Soybean Oil	BCOMBOTR	2056	0.9685	0.0000*	0.0000*	0.0000*	0.1937	0.0000*	0.0000*	0.0000*
Cocoa	BCOMCCTR	1629	0.8758	0.0000*	0.0000*	0.0000*	0.4510	0.0000*	0.6911	0.0000*
Cotton	BCOMCTTR	2067	0.8191	0.0000*	0.0000*	0.0000*	0.5898	0.0000*	0.0060*	0.0000*
Coffee	BCOMKCTR	2077	0.9311	0.0000*	0.0000*	0.0000*	0.3682	0.0000*	0.7159	0.0000*
Sugar	BCOMSBTR	2081	0.9538	0.0000*	0.0000*	0.0000*	0.5789	0.0000*	0.0000*	0.0000*
Wheat	BCOMWHTR	2071	0.9892	0.0000*	0.0000*	0.0000*	0.0679	0.0000*	0.3793	0.0000*
Multi-commodities (Agriculture)	BCOMAGTR	2065	0.9156	0.0000*	0.0000*	0.0000*	0.3683	0.0000*	0.6541	0.0000*
Multi-commodities (Grains)	BCOMGRTR	2070	0.9124	0.0000*	0.0000*	0.0000*	0.3733	0.0000*	0.3724	0.0000*
Multi-Commodities (Soft)	BCOMSOTR	2069	0.9153	0.0000*	0.0000*	0.0000*	0.4753	0.0000*	0.6679	0.0000*

Table 2.11: Results of the persistence of tracking error

This table summarizes the results of the persistence of TE of agricultural ETCs. We examine the persistence through an autoregressive model where the TE(t) is assumed to be dependent on TE(t-1) and TE(t-2). This study models the error variance using a GARCH (1,1) process. The table summarizes the values of α, β1 and β2 coefficients, respectively. Distributions of α, β1 and β2 indicate the number of positive and significant p values (+)/ number of p values not significant (0)/ and the number of negative and significant p values (-). The significance is determined at the 5% significance level.

Commodity	No of Funds	Constant (α)	Distribution of α +/0/-	β1	Distribution of β1 +/0/-	β2	Distribution of β2 +/0/-
Cocoa	8	0.0089	(8,0,0)	-0.0205	(2,5,1)	-0.0094	(2,5,1)
Coffee	5	0.0119	(5,0,0)	0.1859	(4,1,0)	0.0863	(3,2,0)
Corn	5	0.0141	(5,0,0)	0.0153	(2,3,0)	0.0192	(0,5,0)
Cotton	6	0.0129	(6,0,0)	0.0651	(2,4,0)	0.0359	(1,4,0)
Rough rice	3	0.0089	(3,0,0)	-0.0321	(0,3,0)	0.0498	(0,3,0)
Soybeans	4	0.0126	(4,0,0)	0.0461	(1,3,0)	0.0266	(0,4,0)
Soybean Oil	1	0.0189	(1,0,0)	0.0640	(1,0,0)	0.0155	(0,1,0)
Sugar	5	0.0142	(5,0,0)	0.0124	(1,4,0)	0.0349	(1,4,0)
Wheat	6	0.0130	(6,0,0)	0.0283	(1,5,0)	0.0243	(0,6,0)
Multi-Commodities	19	0. 0104	(19,0,0)	0.0098	(1,18,0)	0.0113	(2,17,0)

Chapter Three

Coffee, Orange Juice and Milk: What is Missing in Your Futures Contract Portfolio?

3.1. Introduction

Futures contracts on agricultural commodities have been established and successfully traded for several decades now. Traditionally, commercial investors exposed to price risk related to agricultural commodities were the dominant investors in commodity futures markets before 2000. The commercial investors used commodity futures contracts to hedge their price risk and to smooth the revenue from volatilities in commodity prices. Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) find that commodities have either negative or zero correlation structure with traditional assets such as stocks and bonds. Investing in commodities became increasingly popular among non-commercial investors to achieve their portfolio diversification objectives. Furthermore, large institutional investors played a major role in this financialization process of commodity markets (Basak and Pavlova, 2016; Domanski and Heath, 2007).

Investors can obtain an exposure to the commodity markets either by directly investing in physical commodities or by indirectly investing in derivative products on commodities. Due to the high storage costs involved in obtaining the direct exposure, investors preferred obtaining indirect commodity exposure via derivative products. Financialization of commodity markets has increased the number of positions, turnover and the number of contracts traded in the commodity derivative markets (Zaremba, 2015). The financialization process intertwined the commodity markets with financial markets and investors started considering commodities as an asset class[1] along with stocks and bonds when they decide the strategic allocation of their portfolios.

[1] An asset class consists of assets with similar risk and return characteristics. According to Greer (1997), there are three categories of assets: capital assets, store of value assets and consumable assets. Commodities are consumable assets because their prices are determined based on the demand and supply.

At present, if one looks carefully at the composition of breakfast products, it will be noticed that there are futures contracts on most of the food present. For example, there are futures contracts on coffee, milk, orange juice, sugar, butter and even for wheat included in bread. These agricultural commodities are now well established as investable commodities in financial markets. Despite the fact that the history of tea dates back to the Sheng dynasty of China in 2737 BC (Hall, 2000), tea has been missing from the commodity markets for all these years. Tea does not have either an established price index or a futures contract. It is surprising tea has not yet been elevated into an investable commodity regardless of being one of the oldest as well as one of the highly consumed beverages in the world.

Accordingly, this study has three contributions to the existing literature. First, it provides a detailed overview of the oldest tea auction market in the world, i.e. the Sri Lankan tea market. Second, it examines the feasibility of introducing a futures contract on tea in order to hedge the price risk faced by tea market participants. Since there is no international futures contract on tea if Sri Lanka can introduce a futures contract on tea, it would be useful for all the tea market participants internationally as well. Finally, it investigates whether tea would be an attractive investment asset in the portfolio of any investor.

There are three valid reasons for the choice of Sri Lankan tea market. First, the Sri Lankan tea auction is the oldest auction operating at present with 150 years of history. Sri Lankan black tea is the world's quality tea and earns a premium price in the market. Second, participants in the Sri Lankan tea market face numerous risks. All the tea market participants are exposed to the price risk of tea and hence their income is uncertain. Uncontrollable climate change risk also ultimately increases the volatility of tea prices. Since there are stringent regulatory controls in Sri Lanka on approving a forward contract on tea, these market participants do not have an easy access to the forward market. Therefore, it is interesting and worthwhile to study the Sri Lankan tea market as it is almost free from any derivative contract on tea.

Futures markets play an important role in the development of agricultural commodity markets. According to Atkin (1989), futures markets support establishing fair prices for commodities, create a liquid secondary market and support hedging the price risk associated with commodities. Every futures exchange attempt to introduce contracts on new commodities and/or introduce modifications for existing contracts in order to ensure the survival of the exchange. Therefore, introducing a futures contract on tea would be beneficial for the tea market participants to support mitigate their price risk.

Even before the financialization of commodity markets, Greer (1978) demonstrates that an unlevered portfolio of commodity futures is less risky than a portfolio of stocks. According to Bodie and Rosansky (1980), when an investor allocates 40 percent of its portfolio to commodity futures along with stocks, he could achieve a significant decrease in portfolio risk compared with a portfolio of stocks only. Given the low correlation structure of commodities, an equally weighted portfolio of commodity futures offered the same return and Sharpe ratio as a portfolio of US equities during the period of July, 1959 through December, 2004 (Gorton and Rouwenhorst, 2006). If it is possible to introduce a futures contract on tea, it could be considered as an investment asset on tea by other investors as well. Hence, I investigate whether a futures contracts on tea would be an attractive investment asset in a portfolio of non-tea market participants.

According to the findings of this study, implementing a tea futures contract is not an impossible task, but it is difficult considering the existing structure of the tea market. However, there is a vital need for a risk mitigating method in the tea market. There is an inevitable role to be played by the policy makers of the tea market to create the required infrastructure for a futures market and enhance the awareness of the benefits of a futures contract. The challenge would be how to break the norms of this elite tea industry and standardize it.

The remainder of this paper is organized as follows. Section 3.2 provides an overview of the previous related literature. Section 3.3 introduces the Sri Lankan tea market by explaining its historical development, tea cultivation process and production process along with tea grades. Section 3.4 summarizes the institutional framework of the existing tea market in Sri Lanka and the existing financing mechanism in this market. Section 3.5 presents the data and the sources of data used in the study. Section 3.6 provides the findings and the discussion of the findings. Finally, Section 3.7 concludes the paper.

3.2. Literature Review

3.2.1. Determinants of the success of a futures contract

There is a strand of literature examining the factors that determine the success or failure of a futures contract (Bekkerman and Tejeda, 2013; Black, 1986; Brorsen and Fofana, 2001; Carlton, 1984; Till, 2015; Webb, 2015). According to these previous studies, characteristics of the commodity, characteristics of the cash market and the design of a futures market determine the success of a futures contract. These factors are briefly introduced in this section and Table 3.1 presents a complete list of these characteristics and their references.

[Insert Table 3.1 about here]

The cash market size, volatility of cash prices, level of activeness, degree of buyer concentration and degree of vertical integration are the salient factors in commodity cash markets that determine the suitability of a commodity for a futures contract. The larger the size of the cash market in terms of the value of production, greater the attractiveness to hedgers and speculators (Bekkerman and Tejeda, 2017; Black, 1986; Carlton, 1984; Tashjian and Weissman, 1995). These studies further conclude that there is a positive relationship between price volatility and the success of a futures contract. A commodity with a highly volatile cash market price tends to generate a high level of price risk for the market participants and hence a high demand for hedging.

It is not just the size and the volatility of the cash market that matters, but the degree of activeness also contributes positively for the success of a futures contract. According to Bekkerman and Tejeda (2017), activeness of an underlying cash market represents the degree to which cash market information is available for market participants. Brorsen and Fofana (2001) define the activeness of a cash market as the number of participants and the volume of trading transactions quoted daily. Large losses arising in a large and active cash market due to high volatility in cash prices will motivate market participants to search for better risk management techniques.

Furthermore, the cash market structure also affects the successful development of a futures contract. First, Bekkerman and Tejeda (2017) and Brorsen and Fofana (2001) suggest that the degree of vertical integration in the cash market requires to be low in order to introduce a futures contract successfully. In a market, when there are few pricing points for a commodity without adding value or changing the form of the commodity, such a market is considered to be less vertically integrated (Brorsen and Fofana, 2001). Second, the level of buyer concentration affects the success of a futures contract (Bekkerman and Tejeda, 2017; Brorsen and Fofana, 2001). A cash market is concentrated, when a small number of buyers buys a large proportion of the production. In a buyer concentrated market, trade will likely occur via bilateral trade agreements with buyers. Hence, the price will be determined between the negotiations of the parties to the agreement. For the success of a futures contract, it is essential that commodity prices are determined freely and competitively in the market depending on the demand and supply of each commodity (Carlton, 1984).

Additionally, the commodity itself requires to be homogenous to develop a successful futures contract. Homogeneity is required to be able to standardize the delivery of a futures contract (Atkin, 1989; Bekkerman and Tejeda, 2017; Brorsen and Fofana, 2001). A futures contract is a contract to deliver a commodity of an agreed upon quality in the future. If the commodity is not homogenous, it is difficult to establish delivery standards because a single futures contract can deliver only a single grade of a commodity.

The characteristics of the futures market that determine the success of a futures contract are availability of cross-hedging, liquidity cost of the cross-hedging, contract design, need for commercial hedging and ability to attract speculators. The cross-hedging futures contracts are the futures contracts on highly correlated commodities which can be used effectively for hedging the risk of a given commodity. If there are any already existing cross-hedging futures contracts, there won't be any necessity for a new futures contract (Black, 1986; Gray, 1966; Webb, 2015). The users of a futures contract will compare the liquidity cost of an own-hedge futures contract with that of a cross-hedge futures contract. If the cross-hedge market is more liquid and less costly compared with own-hedge market, traders will likely to use the cross-hedge product instead (Black, 1986).

In the case of introducing a new futures contract on an asset for the first time, there should be a need for hedging (Cuny, 1993; Gray, 1966; Silber, 1981; Till, 2015; Webb, 2015). High volatility in prices will generate losses for the market participants. If these losses are significant enough, market participants will search for methods to mitigate the price risk. Webb (2015) emphasizes the need of attracting speculators into the market. Speculators take the opposite position of hedgers and provide liquidity to the futures market. If the asset prices are determined transparently and information is publicly available for all the participants, speculators will be more confident to participate in the futures market.

Moreover, Gray (1966) and Webb (2015) highlight the importance of having a good contract design that fulfils the requirements of market participants and the importance of timing when introducing a futures contract. Contract design involves the decision of determining the contract specification regarding the size, delivery date, quality of the products to be delivered and delivery price. To be successful, a futures contract should be either the first contract on a commodity or should have a new contract design on an existing commodity which would be more attractive for the traders than the existing contracts (Cuny, 1993; Economides and Siow, 1985).

There is another argument that the design of the infrastructure in the market also affects the success of a futures contract. Ates and Wang (2005) and Tse and Zabotina (2001) find that the migration from open outcry trading to electronic trading creates a favourable environment for a futures contract due to lowered transaction costs and improved efficiency. According to Frank and Garcia (2009) and Shah and Brorsen (2011), the transition into electronic trading reduces the transaction costs in commodity futures markets. Finally, it is essential to educate the market participants and policy makers about the importance of establishing a futures market and obtain their support when introducing a new futures contract (Till, 2015; Webb, 2015).

3.2.2. Benefits of commodities in portfolio diversification

At first, low correlation structure of commodities encouraged investors to use commodities to diversify their portfolios (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Kat and Oomen, 2006). However, after 10 years from their first paper, Bhardwaj, Gorton and Rouwenhorst (2015) find that correlation between commodities and stocks has now become positive during the financial crisis period whereas correlation between commodities and bonds has continued to be negative. Tang and Xiong (2012) credit the financialization of commodity markets via index funds as the reason for this change in the correlation structure.

There is empirical evidence to show that investment in commodity futures reduces the overall risk of the portfolio (Greer, 1978; Bodie and Rosansky, 1980). Moreover, Fabozzi, Fuss and Kaiser (2008) graphically show an upward shift in the efficient frontier when commodities are included into a portfolio of U.S. and global stocks, bonds and treasury bills. However, Scherer and He (as cited in Fabozzi, Fuss and Kaiser, 2008) find that not all the commodity indices provided statistically significant diversification benefits for an investor during January 1989 to June 2006. As per their results, investment in Deutsche Bank Liquid Commodity Index (DBLCI), Deutsche Bank Liquid Commodity Index – Mean Reversion (DBLCI-MR) and Deutsche Bank Liquid Commodity Index – Optimum Yield (DBLCI-OY) delivered statistically significant diversification benefits for an investor.

Adding alternative assets into the portfolio involves an asset allocation decision among stocks, bonds and other alternative assets. According to Markowitz (1952), investors optimize their investment decision based on the risk and return characteristics of a portfolio. The decision to add commodities into a portfolio will depend on its contribution to the overall portfolio performance but not on the standalone performance of the commodities. Theoretically, adding assets with low or negative correlation should provide diversification benefits for an investor. However, a cross-correlation analysis is not sufficient to reliably test for asset classes.

Huberman and Kandel (1987) propose a regression-based test to examine whether adding alternative assets would expand the efficient frontier of an investor. Their regression method is known as the ‘Mean-Variance Spanning Test’. This method was adopted by previous researchers in order to understand the statistical significance of introducing a new asset into the efficient frontier of an average investor. DeSantis (1995) and Cumby and Glen (1990) examine whether a US investor can benefit by international diversification. Bekaert and Urias (1996), Errunza, Hogan and Hung (1999) and DeRoon, Nijman and Werker (2001) investigate whether investors can improve their mean-variance portfolio by investing in emerging markets. Scherer and He (as cited in Fabozzi, Fuss and Kaiser, 2008) find that commodities, when invested along with US stocks and bonds, improve the risk-return trade off of a portfolio. This study also adopts the Mean-Variance Spanning test in order to examine whether tea can be considered as an asset in an investment portfolio of an average investor.

3.3. Overview of Tea Market in Sri Lanka

In order to familiarize readers about this largely unknown tea market of Sri Lanka, this study provides an overview of the historical evolution of this market, details of the tea cultivation and production process and about the tea grading system adopted in Sri Lanka.

3.3.1. Historical evolution of the tea market

According to Forrest (1967), the history of Sri Lankan tea (then known as Ceylon tea) dates back to before 1867, when the first batch of tea seeds had reached and planted at Royal Botanical Garden at Peradeniya, Sri Lanka in 1839. James Taylor was the first planter who achieved success in planting tea for commercial purposes in 1867. Later, he was acknowledged as the "Father of Ceylon tea" for successfully marking the beginning of an era of a remarkable crop in Sri Lanka. The first lot of Sri Lankan tea shipment (of 10kg) was shipped to London for trade in 1873.

At the beginning, the tea plantation sector was developed under large tea plantation companies owned by British investors and the labour was obtained from South India. After the World War II, the industry structure changed with an increase of Ceylonese owned plantation companies. In 1967, the industry consisted of three main types of companies namely: Sterling companies, Rupee companies and individual Ceylonese ownership companies.[2]

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[2] According to Forrest (1967), the ownership of approximately 600,000 acres of tea land was distributed among Sterling companies (registered in London and predominantly British capital), Rupee companies (registered in Sri Lanka with a mix of British and Ceylonese capital) and individual Ceylonese owned companies (registered in Sri Lanka and only Ceylonese capital). The remainder of the tea land was distributed among tea smallholders. Retrieved from

After becoming independent on 4th February 1948, a nationalist government was elected in 1970. On 16th October 1975, this new government enforced a Land Reform Law which limited the private ownership of land only to fifty acres. Then in 1975, the government nationalized the Sterling and Rupee companies and acquired approximately 415,000 acres of cultivated tea land and associated assets.[3] These lands and assets were then re-distributed, under the "State Land Distribution" Program, among rural individual planters and the rest was allocated to two state corporations namely: State Plantation Corporation and Janatha (People's) Estate Development Board. This nationalization decision changed the ownership structure of the tea market from the dominant British ownership into a majority of Ceylonese tea smallholders and government owned companies.

Under this government monopoly of the tea industry, the Sri Lanka Tea Board was established in 1976 to regulate the tea market.[4] During this period, Sri Lanka started importing tea for blending and re-exporting and produced/exported the first lot of green tea. In 1983, some factories initiated using Cut, Tear and Curl (CTC) machines to manufacture black tea.[5] The CTC method of production is cost effective compared with the orthodox method, but the quality of the tea is compromised.

Despite these developments, under government ownership, the tea industry was confronted with several administrative difficulties, labour problems and financial losses. Hence, government in 1992 and 1993, decided to reverse the nationalization decision of the tea industry. However, the government retained the title to all the tea plantation lands and the

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http://www.historyofceylontea.com/ceylon-publications/other-publications/hundred-years-of-ceylon-tea-1867 1967/quick-view/index.php

[3] Details are retrieved from http://www.pureceylontea.com/index.php/independence-and-after

[4] This timeline information are mostly obtained from 'The History of Ceylon Tea' web site. Retrieved from http://www.historyofceylontea.com/history-of-tea-timeline.html

[5] The traditional method of tea manufacturing is the Orthodox method which is highly labour intensive and time consuming but produces high quality tea in terms of brewing and aroma. The CTC method uses machines, hence less labour intensive, and can produce tea within a lesser time than the traditional method. More details will be discussed under the Section 3.2.

management of the land was handed over to 20 private plantation companies under a long-term lease agreement for land. Accordingly, the tea industry in Sri Lanka now consists of these large private plantation companies, a large number of individual tea smallholders and family owned private tea companies.

3.3.2. Tea cultivation and production process

Tea is an agricultural crop of which both the quality and the quantity of supply are highly dependent on the agro-climatic conditions prevailing at the time of cultivation. There are three tea growing areas in Sri Lanka based on the elevation from the sea level. The high grown area has an elevation of 1200m and above; the medium grown area has an elevation between 600m to 1200m and the low grown area has an elevation from sea level up to 600m. The low altitude areas have an intensive sun light. Hence, tea bushes grow rapidly in the low grown areas and will be suitable for harvesting within about two and half years. The high growth of low grown tea sacrifices the quality compared with high grown teas and earns a low price in the market. Higher the altitude, higher would be the quality of the produced tea but lower the growth of the tea bushes.

There are three important climatic factors required to cultivate tea: soil, temperature and rainfall (Hall, 2000). Tea can be grown in a wide variety of soil, if it has a sufficient level of acidity, nitrogen and gets drained well. Any soil with an acidity level of pH values 4.6 to 6.2 would be appropriate for growing tea. When determining suitable land for tea cultivation, it is essential to consider the depth of soil together with its contents such as gravel and rocks. A temperature level between 13^0 to 30^0 Celsius is required with at least four hours of daily sun light. The ideal rainfall for tea cultivation should be between 1200mm and 3000mm around the year. Concurrently, tea cultivators have a responsibility to manage and preserve the soil in their tea lands in order to avoid soil loss and soil wash that can occur as a result of heavy rainfall.

The tea cultivation process includes several steps such as clearing, preparing, planting, weeding, fertilizing, pruning and plucking. Clearing is the act of removing other trees and bushes on the land and then slopping the land as required for planting tea. It takes approximately 5 to 7 years, after being planted, for the tea bushes to become suitable for commercial exploitation and then remains productive for over 50 years. Then, tea plucking occurs at regular intervals of 4 to 10 days with approximately 50 rounds of plucking per annum. Tea plucking is a labour-intensive process and requires a high level of skill, because picking the right tea bud has a direct impact on the quality of the tea produced. Sri Lanka has a unique advantage of being able to pluck tea throughout the year due to its climate conditions.

Tea production commences as soon as the tea is plucked owing to the perishable nature of fresh tea green leaves. All types of tea whether it is black tea, green tea, white tea or Oolong tea are produced from the tea buds and leaves of the same plant. However, these differences stem from the differences in processing tea. The basic steps in the tea manufacturing process are withering, rolling, fermenting, drying, sorting and grading.

There are two tea manufacturing methods currently adopted in Sri Lanka. Majority of the Sri Lankan tea producers still use the traditional Orthodox method. The traditional method involves processing the whole withered tea leaf into either whole leaf teas or broken leaf teas. Orthodox manufacturing is a batch process which is highly labour intensive and relatively slow compared with CTC method. Therefore, the cost of tea production is high under the orthodox method, but it produces high quality tea with special aromatic qualities and delicate flavours. The high quality of the Sri Lankan orthodox tea justifies earning a higher price for Sri Lankan tea in the global market compared with tea from other origins.

A small proportion of the Sri Lankan tea is produced using the modern and cost-effective CTC method. This method involves continuous processing and automated method of crushing, tearing and curling tea leaves into small granules. CTC machines can process a large quantity of tea green leaves at a relatively low cost and within a reduced time period. The CTC tea is quick to brew, dark and deep in colour but lacks the unique aroma.

3.3.3. Tea grades

Hall (2000) states that different types of tea has different grading systems. Accordingly, green tea and Oolong tea are graded based on quality and black tea is graded based on the size of the tea granule. There is no universally accepted standard grading system for orthodox black tea, but there is a standard grading system for CTC tea (N. De Mel, personal communication, October 26, 2017). However, the grading system of orthodox black tea used by other countries are reasonably similar to the grading system adopted in Sri Lanka.

In the Sri Lankan tea grading system, the 'highest' quality tea range is Flowery Orange Pekoe produced from the tip of the tea bud; the next 'fine' quality range is Orange Pekoe produced from the first small leaf; then the second leaf and rest of the leaves produce further lower quality varieties of Pekoe. The higher the number of letters to a grade, higher the quality of tea and hence higher the price. The orthodox black tea grades adopted in Sri Lanka are summarized in Table 3.2.

[Insert Table 3.2 about here]

3.4. Institutional Framework of Tea Market in Sri Lanka

This section explains the institutional framework of the existing tea market in Sri Lanka. It discusses the role of different market participants and the role of the Colombo Tea Auction (CTA). Furthermore, it identifies the risks faced by each market participant and summarizes the existing financing mechanism in the tea market.

3.4.1. Role of the market participants

There are four main players in the tea market in Sri Lanka: tea cultivators, tea manufacturers, tea brokers and tea buyers (N. De Mel, personal communication, January 24, 2017). Figure 3.1

depicts the value chain of the tea market in Sri Lanka. There are three types of tea farmers namely: corporate cultivators, private tea cultivators and tea smallholders. Corporate cultivators are the large publicly listed plantation companies engaged in both cultivation and manufacturing of tea. These listed plantation companies generally own tea lands of over 100 hectares. Private tea cultivators are mostly family owned companies holding tea lands over 10 acres and hire labour to work in their tea gardens. Some private tea cultivators also own tea manufacturing facilities. A tea smallholder is a tea cultivator who owns tea lands of less than 10 acres.[6] Today, the majority of tea smallholders predominantly exist in Southern and Sabaragamuwa provinces of the country. Generally, they do not have their own manufacturing facilities. Tea smallholders and private tea cultivators who do not have the manufacturing facilities sell their tea green leaves to nearby tea manufacturers either directly or via leaf dealers.

[Insert Figure 3.1 about here]

Leaf dealers provide an intermediary facility by buying tea green leaves from the tea cultivators and delivering them to nearby tea manufacturers. Leaf dealers are required to register and obtain an annual license under the Tea Control Act of Sri Lanka Tea Board. They can sell tea green leaves for three tea manufacturers at the same time. They buy tea green leaves at a price specified by each tea factory and obtain a fee from each factory to cover their transportation costs and a commission of 1 percent of the value of the tea leaves (N. De Mel, personal communication, January 24, 2017).

Tea manufacturers with factories are able to process fresh tea green leaves. They process their own tea green leaves, or the leaves bought from tea smallholders or private tea cultivators. It is mandatory for tea producers to register both tea lands and tea factories at the Sri Lanka Tea Board and they are bound to manufacture tea only in those registered factories.

[6] See the Tea Control Act No. 51 of 1957 of Sri Lanka for further details.

In 2017, there were 720 registered tea factories operating in the country.[7] In practice, there is no any contractual agreement between tea factory owners and leaf dealers regarding the price to be paid for the tea green leaves or regarding the quantity of tea leaves to be supplied.

When tea is produced, producers dispatch samples of produced tea along with the tea consignment to brokers on every Friday. Producers have the choice to select one or many brokers whom they intend to sell their tea. This choice depends on the level of costs (storage, insurance and handling costs) charged by each broker and the percentage of the advance payment made by each broker. If any tea producer requires to change their tea broker, it is essential to submit a "No Obligation Letter" from the previous broker to ensure that he has no due payments to the previous broker (I. Dampella, personal communication, February 15, 2017).

The tea broker is responsible for distributing tea samples to respective buyers, valuing tea samples, classifying samples to the auction, selling tea at the auction, remitting sales proceeds to producers, packaging tea and providing warehousing.[8] There are only eight registered tea brokering companies in Sri Lanka at present. The graded and valued tea samples take approximately two weeks to be included in the tea auction catalogue. In brief, tea brokers handle all the activities related to the tea auction process, provide post-auction services and act as intermediaries between producers and buyers. In return, they charge 1 percent commission on tea sales, Rs. 2 per kg[9] as storage cost until the catalogue date, insurance charges and handling charges from producers (N. De Mel, personal communication, January 24, 2017).

Tea buyers in the auction are two types: local buyers and export buyers. Local buyers buy approximately 10 percent of the produced tea from the auction to sell in the local market

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[7] This static is obtained from the Sri Lanka Tea Board web site www.purecelyontea.com on 8th August 2017.

[8] Tea brokers are regulated by the Licensing of Produce Brokers Act No 9 of 1979, Auctioneers Ordinance & By-laws and Conditions for Sale of Tea at the Auction of Sri Lanka.

[9] Based on the exchange rate prevailing at 10th July 2018 (i.e. LKR 159.286/USD), the storage cost is USD 0.01256 per kg.

and export buyers buy the remainder for exporting either as bulk tea or under different private labels. Tea Board of Sri Lanka will verify whether export buyers meet the minimum criteria required to be an exporter of tea.[10] These criteria include the level of capital invested in the organization, availability and quality of warehousing facilities (for storing, blending and packing) and the services provided for tea tasters. Export buyers are subject to stringent quality controls at the pre-auction, post-shipment, pre- and post-import points as well.

Finally, there are warehouses and packers providing warehousing facilities and packing services to the tea brokers and tea buyers. The ultimate consumers of tea are either local tea lovers in Sri Lanka or international tea lovers in the rest of the world.

3.4.2. Colombo Tea Auction

Tea is currently traded in an auction system established since the beginning of the tea being grown as a commercial crop. Auction is the system adopted for disposing of tea by all producing countries at present. A public tea auction is a physical location where buyers, brokers and sellers meet to buy and sell the tea. The first tea auction in Sri Lanka was held on 30th July 1883 at the premises of Somerville & Company. It was a private auction which sold only five lots of tea directly by the William Somerville, the head of the Somerville & Company. These private auctions emphasized the need to establish a well-organized public auction for tea. As a result, on 18th June 1894, "The Colombo Tea Traders' Association" was formed with the objective of promoting the common interests of sellers and buyers and to uphold the good name of the Colombo Tea Auction (CTA). The ownership of the CTA is vested with the Sri Lanka Tea Board under the Sri Lanka Tea Board Law No. 14 of 1975.

The CTA is the oldest and the largest (in the quantity of tea sold weekly) operational single origin (the CTA sells only the tea produced in Sri Lanka) tea auction in the world at present. The CTA is an open outcry English auction in which the general practice is to bid in

[10] Export buyers are regulated under the Tea (Tax & Control of Exports) Act No 16 of 1959 of Sri Lanka.

an ascending order. Tea brokers catalogue all the tea samples received from producers. Brokers and tasters play a pivotal role in setting up the prices of a tea lot in this auction. The tea tasters working for the tea brokers value the tea samples and decide what should be the probable selling price for that lot. While the tasters working for the buyers value the same tea samples and provide an idea for the tea buyers about the price at which they should buy that tea lot. Then, bidding starts at the lowest price and sells to the highest bidding buyer at the end.

The auction system is expected to set a free and flawless market where prices of tea are determined transparently. Therefore, buyers and sellers can respond positively to the bids depending on their needs. The price of a specific tea grade in an auction depends on the demand for that grade and the supply of that specific grade in that auction. Since there is a large number of tea producers (including public planation companies, private tea companies and individual tea smallholders) in the market, the supply of tea is higher and the price competition in the auction is higher because they will be supplying similar grades of tea. The demand for a specific grade depends on the requirements of the buyers which will vary depending on their operational plans and depending on the volatility of the prices as well. However, the CTA does not allow the seller to control prices except by setting a minimum price to trade a particular lot. The sellers rarely fix a minimum price as they need to sell their consignment at any price due its perishability.

The CTA holds auctions every Tuesdays and Wednesdays (except during Sinhala and Hindu New Year and Christmas weeks), with the low-grown tea being sold on the first day and followed by the sale of high-grown and off-grades on the second day. Approximately, 50 auctions take place within a year. Since this auction is not yet automated, it can trade only an average of 12,500 lots per week or approximately 5 to 7 lots per minute. Sri Lanka sells approximately 98 percent of the produced tea through the Colombo Tea Auction. The remaining 2 percent of the produced tea is sold via private contracts, forward contracts, direct sales and ex-factory sales. Therefore, the auction acts as the major point of disposing of the tea produced in Sri Lanka. Only the well-established companies like Dilmah sell their tea directly under their own brand name both in local and global markets.

However, this traditional auction system creates a burden for the tea auction participants as they must be physically present in the auction room in order to conduct the sale. Therefore, the cost of selling and time spent on selling tea via CTA is high.

3.4.3. Risks faced by the market participants

The main purpose of this section is to summarize different risks faced by the market participants in order to provide the reader with an understanding of their difficulties. However, introducing a derivative contract on tea will not provide solutions to all these risks rather it will provide a hedging opportunity against the price risk only.

The types of risks and the degree of risks faced by each market participant in the tea value chain is different. Table 3.3 lists the risks faced by main participants in the tea value chain in Sri Lanka. Accordingly, weather risk is the main uncontrollable risk faced by all tea cultivators. The changing weather conditions severely affect the quality and the quantity of the tea produced and hence affect the prices and the income that can be generated by selling the tea consignment.

[Insert Table 3.3 about here]

The next significant risk is the price risk. Tea cultivators and producers are largely price takers in the tea market. As mentioned above, the price for produced tea is determined depending on the demand and supply of each grade of tea at the auction. Due to the large number of sellers in the market, they become price takers in the auction market.

On a separate note, private cultivators and tea smallholders selling their tea green leaves to a third-party manufacturer, do not have a great bargaining power over the price of their tea green leaves due to its perishability nature, lack of their own transportation and manufacturing facilities (N. De Mel, personal communication, October 26, 2017). The best choice for these tea cultivators is to sell their tea green leaves to the nearby processor even at a low price before the leaves perish.

Furthermore, both cultivators and manufacturers assume a significant investment risk when they decide to invest in a plantation and/ or in a factory. The cost of cultivating, processing and setting up a tea factory is enormous (I. Dampella, personal communication, February 15, 2017). First, it is essential to prepare the soil and land by planting shade trees, building drains, terraces and roads within the plantation to transport tea and purchase specialized plant and machinery required in the manufacturing process. This investment decision is irreversible because the land prepared for tea may not be suitable for other agricultural crops. Alongside, the plant and machinery used to manufacture tea cannot be used in any other manufacturing processes (I. Dampella, personal communication, February 15, 2017).

Concurrently, there is a legal risk associated with the legal right over the tea lands as well. The public tea plantation companies have only a leasehold right to use the land for planting tea (offered by the government in 1992) over a period of 53 years (N. De Mel, personal communication, October 26, 2017). The government has not yet taken any decision regarding whether to extend this lease period or not. Therefore, these corporate cultivators are reluctant to make any further investments despite most of their plantations now require re-planting of tea plants or their factories require new machineries and equipment.

In addition, cultivators and manufacturers face a funding risk because they have to self-finance the process of growing and manufacturing tea. Corporate cultivators are mainly public listed companies and have access to both equity and debt capital via capital markets. In contrast, private cultivators and tea smallholders are individuals or family growers and only have access to limited funding sources (I. Dampella, personal communication, February 15, 2017).

However, they also can borrow funds from financial institutions but at a higher interest rate than for corporate cultivators. Due to this lack of financial resources or high cost of borrowing, tea cultivators are reluctant to either remove old tea bushes, to re-plant or to modernize their factories.

The large plantation companies also have an operational risk arising due to the shortage of skilled labour. The trade unions of tea workers have strong bargaining power and continuously demand to raise wage rates (N. De Mel, personal communication, October 26, 2017). The cost of producing tea has increased during the past decades due to this increased labour cost. If the management refuses to increase the wage rate, it will likely to result in labour strikes ultimately disrupting operations and creating further losses for these companies.

In contrast, tea smallholders do not face labour strikes because they themselves work in their own tea lands by doing all the activities. Due to the limited funds available, they are unable to hire skilled labour to work in their small gardens (I. Dampella, personal communication, February 15, 2017). On the contrary, this might have an impact on the quality of the plucked tea green leaves and eventually on the quality of the produced tea, if they are not sufficiently skilled to pluck tea.

The tea buyers in the Sri Lankan tea market face a low level threat of new entrants due to two reasons (N. De Mel, personal communication, October 26, 2017). First, tea brokers are not willing to accept bids from a new buyer due to the high risk of default. Second, new buyers will require a greater investment to set up their own tea blending or tea packing facilities, which restricts new buyers entering into the market.

3.4.4. Existing financing mechanism

This section provides an overview of the current financing sources and the financing mechanism used by each market participant in the Sri Lankan tea market. When tea producers send their consignment and samples to brokers, they receive an advance payment from the brokers. Tea brokers value samples based on the recent historical prices received for the respective grade and pay a certain percentage of that value as an advance payment. Tea producers then, in turn, advance the money to smallholders and private cultivators for the tea green leaves they supplied. Tea brokers take approximately 3 to 4 weeks to grade and catalogue these samples in the CTA (N. De Mel, personal communication, January 24, 2017).

After buying, on the next Friday immediately after the auction, tea buyers require to settle 10 percent of their purchase value of tea. The remaining 90 percent of the purchase value requires to be settled on the following Tuesday after the auction. On the 7th day after the auction, the broker has to settle all the money to the producer. If any buyer has not settled the payments by the due date, he is prohibited from trading in the next auction until the due amount is paid off (N. De Mel, personal communication, January 24, 2017). Accordingly, tea producer's and tea broker's exposure to default risk is protected in this auction system.

To protect the income of tea leaf suppliers (tea smallholders and private tea cultivators who do not own a tea factory), the government has enforced a 'Reasonable Pricing Formula'[11] in 1984 (Herath and Weersink, 2009). This formula states the ratio at which the black tea price will be shared among the processor and the green leaf supplier, respectively. At present, the ratio is 32:68 allowing the manufacturers to receive 32 percent of the black tea price as the income for manufacturing tea and tea smallholders to receive 68 percent of the black tea price as their income for selling green leaves. Under this method, the price risk is shared among the tea producer and leaf supplier.

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[11] As Herath and Weersink (2009) mention, the government set a guaranteed minimum price for tea green leaves for the first time in 1968. The guaranteed price for tea green leaf is calculated as the Colombo black tea price minus cost of processing tea minus tea processor's profit divided by 4.5 (i.e. the weight of tea green leaves required to produce one kilo of black tea). In this formula, the entire price risk in black tea prices is passed on to the leaf supplier. In 1978, this formula was modified to provide a guaranteed minimum price for tea leaf suppliers. In 1984, the guaranteed minimum price was replaced by the 'Reasonable Pricing Formula' of 25 percent to 75 percent (i.e. the ratio of sharing black tea price among the tea producer and leaf supplier, respectively). In 1985, this ratio was again changed to 30 percent to 70 percent and in 1987 to 32 percent and 68 percent, respectively.

The large number of tea exporters in the market creates a severe competition among bulk tea exporters to attract buyers. Tea exporters use their extended and flexible credit policy as a marketing tool to attract more buyers. As a result, tea exporters must wait for a long period to collect the due amount from the tea buyers. Though this credit policy would be favourable for the buyer, it generates a harmful default risk exposure for tea exporters (N. De Mel, personal communication, January 24, 2017). As a result of this extended credit policy, the Sri Lankan tea exporters were highly affected during the recent financial crisis in 2008 when most of the international tea buyers defaulted on their payments.

3.5. Data

This study uses average monthly tea prices obtained from the Global Economic Monitor database of the World Bank. This is the arithmetic average tea price quoted at the main tea auctions: Mombasa, Colombo and Culcutta. These are the average monthly prices for all the black tea grades. I collected data on Standard & Poor 500 (S&P 500) index, Bloomberg Barclays US Corporate Total Return index, Bloomberg Barclays US Treasury Total Return index, Gold and Silver spot prices in USD from the Bloomberg. The 90-day monthly Treasury Bill rate of US is obtained from the Kenneth French website. [12]

The data on the historical evolution and institutional framework of the Sri Lankan tea market is obtained, in the main, from the Statistical Bulletin 2011 and 2015 published by the Sri Lanka Tea Board and from the Annual Reports of the Central Bank of Sri Lanka. The details about the time line events, tea cultivation and manufacturing process have been collected from the web sites of the Sri Lankan Tea Board and Dilmah Ceylon Tea Company PLC. Furthermore, I have gathered data from personal communications as well.[13]

[12] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html for further details.

[13] I have collected data via interviews and email communication with Niraj De Mel (A former Chairman of the Sri Lanka Tea Board, professional tea taster with over 38 years of experience in the industry and the pioneer of The Mel's Tea Academy)

As a first step, it is essential to compare the tea market volatilities with the volatilities of 14 other agricultural commodities for which futures contracts already exist. I have selected 14 commodities included in the Bloomberg Agriculture Total Return index ((AgriTR Index) and the list of these commodities are presented in Table 3.4. The daily prices of these indices are collected from January 1991 (this is the earliest date on which index data is available) to October 2017 from the Bloomberg.

[Insert Table 3.4 about here]

3.6. Feasibility of Introducing a Futures Contract on Tea

This section presents the results and the discussion of the findings. First, I examine the commodity characteristics and cash market characteristics of tea to determine whether introducing a derivative contract, specifically introducing a futures contract on tea, would be feasible. In the Literature Review section above, I have listed cash market characteristics, commodity characteristics and futures market characteristics that determine the success of a new futures contracts. This section will discuss these characteristics related to the Sri Lankan tea market to decide whether tea would be an appropriate commodity for a futures contract.

3.6.1. Price volatility in the cash market

In order to analyse the price volatility of tea, I compare the volatility of tea returns with the volatilities of 14 other agricultural commodities included in the AgriTR Index (See Table 3.4). All these commodities have pre-existing futures contracts in the market. Table 3.5 presents the annualized volatilities of these agricultural commodity indices and tea returns in the auction market. During the period from 1991 to 2017, the annual volatilities of all agricultural commodities have experienced fluctuations in every year.

[Insert Table 3.5 about here]

and with Isuru Dampella (Managing Director at New Diyagala Tea Factory, Sri Lanka). Sampath Perera, Kanchana Rasanjalie and Devika Jayathilake provided me the statistical reports and information available at the Sri Lanka Tea Board.

During this period, coffee (33 percent) and orange juice (30 percent) have reported the highest average annualized volatility, respectively. The live cattle (13 percent) and feeder cattle (14 percent) have reported the lowest average annualized standard deviations, respectively. In contrast, tea has reported an average annualized volatility of 18 percent which is above the average volatilities of feeder cattle and live cattle. At present, there are successfully trading futures contracts on both feeder cattle and live cattle even when the volatilities of these commodities are comparatively lower than tea. Therefore, one can argue that the volatility of tea is sufficient to justify introducing a futures contract on tea.

The volatility of tea prices would also be affected in the future due to expected climate changes. Climate change will inevitably impact many regions of the world and adversely affect the agriculture sector and hence the food industry. Gunathilaka, Smart and Fleming (2017) conclude that tea production in Sri Lanka will be negatively affected by the predicted long-term changes in rainfall and temperature levels. Jayasinghe and Kumar (2019) find that expected climate change will have a negative effect on the habitat suitability of tea in Sri Lanka by 2050 and 2070. This detrimental climate change will most likely affect the future production of tea and hence increase the price volatility in the Sri Lankan tea market.

3.6.2. Size of the cash market

The next factor in consideration is the size of the cash market. In 2016, the world tea production volume (black tea, green tea and all other types) reached to 5.73 million tonnes.[14] Figure 3.2 depicts the world tea production (in percentage) of the main tea producing countries. According to this graph, China and India have been the major tea producers in the world during last decades. Thereafter, Kenya, Sri Lanka and Japan contribute to tea production as the third, fourth and fifth largest producers in the world, respectively. However, due to the high level of

[14] World tea production and consumption data are obtained from the "Current market situation and medium-term outlook report" of the 23rd Session of the Intergovernmental Group on Tea held on 17th to 20th May, 2018 at Hangzhou, The People's Republic of China. Retrieved from http://www.fao.org/economic/est/est-commodities/tea/tea-meetings/tea23/en/

domestic consumption of tea in China and India, these countries are not the largest tea exporting countries in the world.

[Insert Figure 3.2 about here]

Figure 3.3 shows that, in 2016, Kenya, China and Sri Lanka were the three largest tea exporting countries, respectively. The export percentage of China (18.2 percent) is closer to that of Sri Lanka (16.9 percent) in 2016. During the last decade, Sri Lankan tea production has dropped but since Sri Lanka exports majority of its tea production, the country has continued to secure its position in the tea export market. Accordingly, total tea exports in Sri Lanka was 282.4 million kilogrammes in 2018 compared with 289.0 million kilogrammes in the previous year and the tea export income of Sri Lanka was USD 1428 million in 2018.

[Insert Figure 3.3 about here]

Figure 3.4 compares the world production values of coffee, orange juice, milk and tea for the time period between 1991 and 2016. The value of the world tea production shows an increasing trend and has been USD 11343 million in 2013. The recent statistics of FAO reports the global value of tea production as USD 15249 in 2016. According to the graph, the value of tea production is comparatively closer to that of coffee.

[Insert Figure 3.4 about here]

Amidst all the forecasts about the adverse impact of climate change on the agriculture sector, Intergovernmental Group on Tea of 2018 estimates that the world black tea production will still increase by 2.2 percent annually from 2018 to 2027 and the world green tea production will still increase by 7.5 percent annually from 2015/17 to 2027.[15] Therefore, the size of the cash market of tea is expected to grow continuously into the future even among the price volatilities that might arise due to climatic changes. Hence, this study asserts that the size of

[15] World tea production forecasts also are obtained from the "Current market situation and medium-term outlook report" of 23rd Session of the Intergovernmental Group on Tea held on 17th to 20th May, 2018 at Hangzhou, The People's Republic of China. Retrieved from http://www.fao.org/economic/est/est-commodities/tea/tea-meetings/tea23/en/

the world tea market and the size of the cash market of Sri Lanka would be adequate to introduce a futures contract on tea.

3.6.3. Activeness of the cash market

In Sri Lanka, CTA is the main mode of disposing of the tea production and approximately 98 percent of the tea supply is sold via auction (N. De Mel, personal communication, October 26, 2017). In 2018, Sri Lanka sold in total 281.8 million kilograms of tea via the CTA. As mentioned above, CTA holds approximately 50 auctions per year (every week) and the tea market is active throughout the entire year. The auction continues selling tea lots for two consecutive days every week.

The tea market in Sri Lanka consists of 720 registered manufacturers, 340 exporters, 135 importers, 238 warehouses, 426 packers and 333 green leaf dealers at present.[16] The large number of constituents in this market emphasizes on the value of this industry and its contribution to the socio-economic environment. Based on this evidence, I conclude that the Sri Lankan tea market is considerably active and liquid to support a futures contract on tea.

3.6.4. Product homogeneity

This study measures the product homogeneity by the effectiveness of the grading system. According to Brorsen and Fofana (2001), a commodity should be effectively graded to represent the variation in prices and this grading system should be commonly accepted and adopted by all the participants in the market. With regard to orthodox black tea, there is no universally accepted single grading system, whereas there is a standard grading system for CTC black tea (N. De Mel, personal communication, October 26, 2017). Countries like Sri Lanka and India producing orthodox black tea, use a grading system which is fairly similar to each other. As mentioned in Table 3.2, the grading nomenclature of orthodox black tea creates

[16] These statistics are obtained from the Sri Lanka Tea Board web site www.purecelyontea.com on 8th August 2017.

grades based on the leaf size. Mainly there are two grades: whole leaf grade or broken leaf grade and a variety of sub grades under each category.

The tea-grading system in Sri Lanka is well established as well as prevalent among the tea buyers. Conversely, these substantial sub-grades create a significant market segmentation and creates an obstacle to financialize the tea market. This obstacle exists not only in the Sri Lankan tea market but in all the tea producing countries as well (Besky, 2016). The larger the number of market segments, reduces the size and activity of each sub-grade and hence lowers the likelihood of a successful single futures contract on tea.

The quality of tea varies depending on climatic condition, region and even, in the same region, from one harvest to the next. If the quality of the produced tea is not exactly the same as the promised grade for delivery, the futures contract may not be able to deliver the tea. This heterogeneity in the grades can be overcome either by designing a futures contract with a premium or discount system based on the variation of tea grades or by designing a financial futures contract based on a tea price index without physical delivery. However, establishing a standard grading system for orthodox black tea would ultimately pave the way for effectively automating the tea auction system.

3.6.5. Underlying market structure

For a futures contract to be successful, cash market needs to be less vertically integrated and less buyer concentrated. According to Brorsen and Fofana (2001), the degree of vertical integration depends on the number of pricing points of a commodity. In the tea market, first, tea smallholders and private cultivators sell tea green leaves to the tea manufacturer. When tea is produced, it is sold either in the auction or directly via private contracts. In private direct sales contracts, the price of tea will be determined via a bargaining process between the buyer and the seller. The income of the manufacturers and cultivators depends on the tea prices earned in the auction. All the local buyers and export buyers can directly buy tea from the auction.

The price of produced tea is solely determined at the CTA. Accordingly, the pricing mechanism of the produced tea in Sri Lanka is considerably vertically integrated, the CTA being the major pricing point for bulk tea.

In contrast, Sri Lanka exports tea in different forms such as bulk tea, value added tea, tea packets, tea bags, instant tea or green tea. Tea exporters determine the price of their bulk tea, tea packets, tea bags, green tea depending on the prices at which they buy tea from the auction. Furthermore, exporters have the opportunity to add a premium for the price when they export under their own private labels or when they export value added tea. The export price of these valued added tea products is determined by the exporter.

The concentration of buyers in the market is defined as the percentage of the commodity handled by the largest players in the market (Brorsen and Fofana, 2001). In the global tea market, buyers are highly concentrated and hence have a high bargaining power (Thushara, 2015). There are only four major multinational companies that account for approximately 80 percent of the international tea trade (Ganewatta and Edwards, 2002). This high level of buyer concentration could overcome by enhancing the access to this auction by introducing an electronic trading platform.

3.6.6. Availability of cross-hedging

It is necessary to identify the cross-correlations between the assets under consideration and other closely related assets to determine whether cross-hedging will be effective. This study estimates the correlation between coffee prices and tea prices. The world average tea prices, tea prices at the Colombo Tea Auction, world average coffee Arabica prices and coffee Robusta prices are obtained from the Global Economic Monitor Commodities database.[17] In addition, I have collected the Composite Coffee Price Index[18] data published by the International Coffee

[17] The world average tea and coffee prices are the nominal prices in USD per kg.

[18] Composite Coffee Price Index is calculated by the International Coffee Organization as the weighted average composite price of Brazilian natural Arabica coffee prices (31 percent), Colombian mild Arabica coffee prices (12 percent), other mild

Organization. The data consists of monthly prices for the period from January 1991 to October 2017.

Table 3.6 shows the cross-correlations between tea and coffee time series data. Panel A of the table uses data obtained from the Global Economic Monitor database and Panel B uses coffee price data obtained from the International Coffee Organization. According to the results in Panel A, world average tea price is positively correlated with world average Arabica coffee prices (0.10) and with world average Robusta coffee prices (0.07). The Colombo tea prices are positively correlated with coffee Arabica prices (0.06) and slightly negatively correlated with coffee Robusta prices (-0.01). Furthermore, in Panel B, both world average tea prices and Colombo tea prices show a low positive correlation (less than 0.01) with the Composite Coffee Price Index.

[Insert Table 3.6 about here]

Theoretically, assets with negative correlation provide the best diversification benefits. According to the findings of this study, futures contracts on coffee Arabica or coffee Robusta will not provide an effective cross-hedging opportunity for tea market participants due to their positive and low correlation values with tea.

3.6.7. Need for hedging

According to Webb (2015) and Till (2015), one of the major factors that determines the success of a futures contract is the need for hedging. A futures contract is a mechanism to hedge the price risk. In the Sri Lankan tea market, producers and exporters have to undergo a strict approval process to enter into a forward contract. Therefore, the use of forward contracts to mitigate price risk is not practically adopted in the Sri Lankan tea market. Furthermore, the global tea market is also free from futures contracts on tea.

Arabica coffee prices (23 percent) and coffee Robusta prices (34 percent). The coffee prices are collected from USA, France and Germany spot markets. The weighting of each group is reviewed every two years.

Theoretically, a necessity of a futures market arises due to the limitations in the forward market. The unavailability of forward contracts emphasizes the economic need of introducing a futures contract on tea. A futures contract on tea will provide an effective hedging mechanism for the tea market participants to mitigate their price risk. Due to the large number of producers and exporters involved in this market, if introduced, one can expect a futures contract on tea to achieve a considerable level of trading volume.

3.6.8. Interest of speculators

A successful futures contract is required to fulfil both the need for hedging and be able to attract speculators (Till, 2015; Webb, 2015). There are three aspects to attract speculators: there must be a community of risk takers, there must be a level playing field for speculators and speculators must have the ability to manage the price risk by taking the other side of the hedger’s position (Till, 2015).

Due to the increased popularity of adding commodities into an investment portfolio to achieve diversification, it is justifiable to expect a futures contract on tea attracting a group of speculators or investors internationally. Tea buyers in this market would be willing to participate in a futures market to hedge the price risk faced by producers. Since most of these international tea buyers sell blended tea, if the prices at CTA are high, they have the ability to buy tea from another auction at a comparatively lower price than those at CTA and blend in a different recipe. This substitution effect of tea might slightly reduce the demand for the Sri Lankan tea.

However, there is a limit to this substitution. For example, if a multinational tea company has sold tea bags and tea packets at a particular quality and taste, they have to maintain the same quality and taste in their blended tea every time to retain their customers. In that case, even if Sri Lankan tea is expensive, they are unable to completely change their blending formula and avoid buying from the CTA.

If this study can provide empirical evidence on the diversification benefit of tea as an investment asset in the portfolio of an average investor, the findings of this study would be beneficial to attract the interest of general investors to this market. Therefore, this study discusses the diversification benefits of tea in a later section.

3.6.9. Public order flow

Another vital factor that must exist in the cash market to introduce a futures contract is the free public flow of information (Till, 2015; Webb, 2015). As mentioned above, tea prices and other tea market related statistics are freely available for anyone via the web site of the Sri Lanka Tea Board.[19] In addition, the annual statistics about tea production, auctions, exports and other information about the industry is freely available in the Annual Report of the Central Bank of Sri Lanka.[20]

Nevertheless, the problem lies in the price discovery mechanism for the tea in this auction system. Not only in the Sri Lankan tea industry but also in the tea auctions in India and Kenya, there is a reluctance emanating from the market participants avoiding the transformation of these auction systems into the next level either by introducing a digital auction system or by financializing tea as an investable commodity. Besky (2016) explains the issues in the infrastructure of the Indian tea market that limits the financialization of this commodity from sociological and anthropological perspectives. As Besky (2016) correctly points out, the tea price is not determined purely based on the demand and supply for a specific grade in an auction. The stories about the price and mutual understanding between buyer-brokers and seller-brokers in a way affect the price discovery process in this open outcry system in the prevailing tea auctions. That study further emphasizes the importance of disentangling

[19] Please refer to http://www.srilankateaboard.lk/ for details about the Sri Lankan tea market and for weekly auction statistics.

[20] Please refer to https://www.cbsl.gov.lk/en/publications/economic-and-financial-reports/annual-reports for online version of these annual reports.

tea from being socially embedded with the market participants into a standardized commodity for which the price will be determined in a more rational and standardized manner.

During my personal communication with the tea market participants, I realized this scenario prevails in the Sri Lankan industry as well. Though the information about the auction is freely available for anyone with an interest, the transparency of the price discovery process in the CTA is questionable. As mentioned above, there are only eight registered tea brokering companies in Sri Lanka and these brokers represent both buyers and the sellers in the auction. Thus, the buyers-brokers and seller-brokers are highly interconnected and their level of involvement and the understanding in the tea industry is also high. As Besky (2016) explains, I also discovered that this interconnectedness and communication flow between buyers-brokers and seller-brokers hinders the transparency in the price generating process in CTA. Therefore, I note the importance of enhancing a transparent price discovery process for tea in order to improve the quality of public order flow.

3.6.10. Regulatory support

Furthermore, it is essential to have regulatory support to introduce a futures contract on tea. First, the government and the regulators of the tea market need to understand the economic contribution of introducing a futures contract on tea to the Sri Lankan economy. At present, Sri Lanka does not have a futures exchange on equities. Therefore, investors and the general public in Sri Lanka do not have any experience of trading and using a futures contract yet. The lack of financial literacy of the derivative markets has already delayed the evolution of this tea market.

According to my findings, I would suggest that market regulators, the government and even the academics in Sri Lanka should be responsible and initiate the process of educating the market participants and the general investor community regarding the benefits of a futures contract and how to use this futures contract to mitigate price risk. The involvement of the government in this process will definitely enhance confidence among the existing tea market participants and positively change their attitudes toward this transformation of the tea market.

3.6.11. Trading platform

Finally, the CTA is the only tea auction available in Sri Lanka and it is the only trading place for Sri Lankan tea. As CTA sells only Sri Lankan tea (earlier known as Ceylon tea), it is considered as a single-origin tea auction. This is not an automated trading platform. Therefore, the auction is held for two consecutive days to sell all the tea lots catalogued in that week. Since the auction is based on the open outcry system, auction participants must physically present in the auction floor to do a trade.

There is a substantial resistant from the auction participants for the conversion of this market into an electronic trading platform. The India Tea Board attempted digitizing the tea auction by introducing teaauction.com in 2002. It was an online platform introduced for trading tea. After few years, this attempt became a failure as the Indian Tea Board was unable to attract a sufficient number of traders and subsequent sales volume for this system to be a success. The fear of losing power and social status in the auction and fear of losing job opportunities are the reasons why tea auction participants did not support this transformation process.

Nevertheless, Frank and Garcia (2009) and Shah and Brorsen (2011) find that the automation of the auction process may reduce the transaction costs in a commodity market. Furthermore, Besky (2016) is also of the opinion that converting this traditional auction system into an electronic trading platform will standardize the price discovery process of tea and will necessarily create a favourable environment for introducing a futures contract on tea.

Finally, Table 3.7 summarizes the degree to which the Sri Lankan tea market meets these success criteria in introducing a futures contract. In summary, the Sri Lankan tea market has a sufficient level of price volatility, a considerable cash market size in terms of trading volume, number of participants and the production value of tea. This is a highly active tea auction market with continuous trading throughout the year. Tea prices are determined in the auction market even though the transparency of the price formation is questionable. Auction information and tea market information are freely available to the public. Market participants have an unfulfilled need for hedging the price risk they face in the auction. Furthermore, there is a need for a futures contract on tea as cross-hedging using coffee would not be effective. These characteristics of the tea market supports the idea of introducing a futures contract on tea. In contrast, there are several factors that might delay the successful introduction of a futures contract on tea. The major concerns are the lack of universally accepted grading system, lack of standardization and transparency in the price formation process, lack of support from government and market regulators.

[Insert Table 3.7 about here]

3.7. Diversification Benefits of Tea

This section investigates the diversification benefits of tea as an investment asset in a portfolio along with traditional investment assets. The first section explains the methodology and the later section presents the results and discussion of the findings.

3.7.1. Methodology

The diversification benefits can be achieved only by combining assets with negative correlation structure. The ultimate objective is to create an optimal portfolio of assets that will optimize risk-return expectations of an investor. In this analysis, first, I calculated the annualized mean return and standard deviation of the tea and 14 other agricultural commodities (listed in Table 3.4). In addition, I calculated the Sharpe ratios and correlations of these other agricultural commodities with tea. Second, I calculated correlation of tea returns with the returns of S&P

500 index, Bloomberg Barclays US Corporate Bond index, Bloomberg Barclays US Treasury Bond index, Gold and Silver spot price indices (quoted in USD).[21]

Third, I developed the efficient frontier in three different scenarios and compared the performance of these portfolios. Case 1 includes only stocks, corporate bonds and treasury bonds. Case 2 includes a portfolio consisting of stocks, corporate bonds, treasury bonds and precious metals (gold and silver). Case 3 adds tea along with all above-mentioned assets. According to Black (1972), given any two envelope portfolios, efficient frontier of all portfolios can be developed because efficient frontier includes all the convex combinations of these two envelope portfolios. I estimated investment proportions of the global minimum variance portfolio (GMVP) and the market portfolio.[22] I derived the GMVP using the following formula.

$$X_{GMVP} = \frac{1_{row}S^{-1}}{1_{row}S^{-1}1_{row}^{T}}, \tag{3.1}$$

where X_{GMVP} is a matrix of the weights in GMVP, $1_{row}$and 1_{row}^{T} is a row vector including value 1 only and the transpose of that row vector. Finally, S^{-1} is the inverse of the sample variance-covariance matrix.

The investment proportions of the market portfolio are calculated using the following formula.

$$X_{Market} = \frac{S^{-1}\{E(r)-c\}}{\sum[S^{-1}\{E(r)-c\}]}, \tag{3.2}$$

[21] Standard and Poor's 500 (S&P 500) index is the total return index of the 500 largest market capitalization companies in US. Bloomberg Barclays US Corporate Bond index measures the investment grade, fixed-rate, taxable corporate bond market. It includes USD-denominated securities publicly issued by US and non-US industrial, utility and financial issuers. Bloomberg Barclays US Treasury Bond index measures USD-denominated, fixed rate nominal debt issued by the US Treasury. This index excludes Treasury Bills but includes Treasury Bonds with a maturity period ranging from more than one year up to 10+ years. Gold and Silver prices are quoted in USD in US market.

[22] GMVP is the portfolio with the lowest possible minimum variance for a given level of return. Market portfolio is an efficient portfolio which consists of all the risky assets.

where X_{Market} is a matrix of the proportions in the market portfolio, S^{-1} is the inverse of the sample variance-covariance matrix, $E(r)$ is the expected return of the portfolio and c stands for the risk-free rate of return. Then, I calculated a series of portfolio returns and standard deviations assuming different combinations of GMVP and market portfolio in three scenarios and graphically presented the efficient frontier of each scenario.

Markowitz (1952) suggests that investors can optimize their investment decision based on the risk and return of the portfolio only. Later, other researchers developed various portfolio optimization models based on mean-variance criteria.[23] DeMiguel, Garlappi and Uppal (2009) compare the efficiency of 14 portfolio optimization strategies with the naive diversification strategy (equal weights). They find none of these 14 strategies consistently performed better than the naive strategy. Therefore, this study also creates an equally weighted portfolio under each case and compares its performance with the GMVP and the tangent portfolio.

Finally, I tested whether an average investor can improve his or her portfolio performance by adding tea as an asset. This is tested statistically by using the Mean-Variance Spanning test which was first introduced by Huberman and Kandel (1987). This study considers a US investor to represent an average investor because US has both well-developed and liquid equity and bond markets. Previous researchers also adopted a US investor to represent an average investor (Bekaert and Urias, 1996; Cumby and Glen, 1990; DeRoon et al., 2001; DeSantis, 1995; Errunza et al., 1999) with regressing the excess return of tea on the excess returns of other traditional assets added into the portfolio as follows.

$$(R_i - R_f) = \alpha + \sum_{j=1}^{J} \beta_j (R_j - R_f) + \varepsilon, \tag{3.3}$$

where R_i is the return on tea, R_f is the risk-free rate (90 days Treasury Bill rate), R_j is the return on other assets (return on S&P 500 index, return on Bloomberg Barclays US Corporate Bond

[23] See Kolm, Tutuncu and Fabozzi (2014), Loistl (2015), Markowitz (2014), Rubinstein (2002) and Steinbach (2001) for more details on these different models of mean-variance-optimization, limitations in these models and the approaches developed to encounter these limitations.

index, return on Bloomberg Barclays US Treasury Bond index, return on gold and silver) and ε is the error term. Every β_j coefficient is interpreted as weights of traditional assets that can be used to replicate the return of tea. This study tests the null hypothesis $H0: \alpha = 0$. If the constant term (α) is statistically significant and not equals to zero, there is a significant portion of the tea return unexplained by the traditional assets. I can then consider tea as a separate investment asset in the portfolio.

3.7.2. Results

First, this section presents the descriptive statistics of the agricultural commodities in Table 3.8. During the period from January 1991 to October 2017, most of these commodities earned a negative mean return. Soymeal and soybean report the highest mean returns of 7.30 percent and 5.50 percent, respectively and tea reports a mean return of 1.93 percent. The lowest mean returns of -7.70 percent and -7.21 percent are reported for wheat and lean hogs, respectively. Coffee and orange juice have the highest volatility of returns of 35.84 percent and 31.02 percent, respectively. Tea reports the third lowest volatility of return of 16.81 percent. However, it is noteworthy that feeder cattle (14.44 percent) and live cattle (13.86 percent) have lower volatilities than tea but have successfully trading futures contracts in the market.

[Insert Table 3.8 about here]

The Sharpe ratio of a commodity explains the level of excess return (commodity return – risk-free return) per unit of risk. Most of these agricultural commodities including tea report negative Sharpe ratios because of negative excess returns which are not meaningful to interpret. The results reveal that tea has a positive correlation with all other agricultural commodities except lean hogs. Therefore, adding tea into a portfolio along with these agricultural commodities would not convey any diversification benefits for an investor.

Subsequently, Table 3.9 summarizes the descriptive statistics and correlation statistics of tea, stocks, corporate bonds, treasury bonds, treasury bills, gold and silver for the period from January 1991 to October 2017. The portfolio includes gold and silver as precious metals are now considered to provide a hedge against stocks and bonds.[24]

[Insert Table 3.9 about here]

Compared with these traditional assets and precious metals, tea has the lowest return (1.96 percent) and the second highest volatility (16.78 percent) which is below the highest volatility of silver (30.03 percent). Due to its lower mean return than the average risk-free return, tea reports a negative Sharpe ratio (-0.0375), whereas all the other assets report positive Sharpe ratios. However, tea has a low positive correlation (less than 0.10 approximately) with all the assets except with government securities. The results show that tea is negatively correlated with treasury bonds (-0.1032) and treasury bills (-0.0183). Hence, it acts as a hedge against the government securities in this case.

Thereafter, Figure 3.5 presents the efficient frontiers generated for the above mentioned three scenarios. This graph does not depict a significant change in the risk and return of the portfolios available for a low-risk averse investor (i.e. the portfolios located at the upper end of the frontiers). In contrast, there is a significant shift in the GMVP of each case. The risk and return of the GMVP under case 2 (including gold and silver) is slightly lower than the risk and return of the GMVP under case 1 (including traditional assets only). By adding tea in case 3, I could create a GMVP which has a significantly lower risk compared with both case 1 and 2. This graphical representation shows a shift in the efficient frontier from the lower end including the GMVP.

[Insert Figure 3.5 about here]

Table 3.10 presents the risk-return characteristics of the GMVP, tangent portfolio and for an equally weighted portfolio in each case. According to my findings, the GMVP invests

[24] Gold acts as a hedge and a safe haven for stock in US, UK and German (Baur and Lucey, 2010), in major European markets and US (Baur and McDermott, 2010), in EMU, Indonesia, Russia and Turkey (Beckmann, Berger and Czudaj, 2015).

more than 90 percent in Treasury bonds, approximately 12 percent in stocks and includes a short selling position of less than 13 percent in corporate bonds. In both Case 2 and 3, the GMVP invests 3 percent and 2 percent in precious metals, respectively. In Case 3, the GMVP invests 7 percent in tea along with other assets. Adding tea has reduced the risk of the GMVP compared with both Case 1 and 2. The GMVP portfolio in Case 3 reports a mean return of 5.31 percent and a standard deviation of 0.0405 percent. The coefficient of variation (CV)[25] is lowest (0.76 percent) for the GMVP in Case 3 after adding tea into the portfolio. Therefore, this study concludes that tea would provide diversification benefit to the portfolio of a high-risk averse investor. However, the economic significance of this benefit is questionable as the reduction in the risk is numerically low.

[Insert Table 3.10 about here]

As per these results, the tangent portfolio invests 11 percent in stocks, approximately 40 percent in corporate bonds and 50 percent in Treasury bonds. Furthermore, the tangent portfolio invests only 2 percent in silver and holds a short selling position of 3 percent in gold. The tangent portfolio takes a short selling position in tea by short selling only 1 percent of the value. In contrast to the GMVP, adding precious metals and then tea into the tangent portfolio increases the risk of that portfolio instead of reducing the risk. The CV is highest (0.87 percent) after adding tea into the tangent portfolio. Accordingly, there is no diversification benefit generated by adding tea into the tangent portfolio. Hence, one can conclude that for a low-risk averse investor investing in the tangent portfolio, tea will not provide any diversification benefits.

For the equally weighted portfolio, adding gold and silver increases both the portfolio returns and risk significantly. In Case 3, the equally weighted portfolio with tea reports a mean return of 5.22 percent and a risk of 0.21 percent. Adding tea reduces the CV of the equally

[25] Coefficient of variation (CV) is the ratio of standard deviation for the mean. It shows the risk per unit of return. Theoretically, lower the CV is better.

weighted portfolio compared with Case 2. Therefore, I conclude that tea would provide diversification benefit for an average investor who simply follows a naive strategy.

Finally, the findings of the mean-variance spanning test are presented in Table 3.11. This test examines whether tea can be considered as a separate asset in a portfolio. The results suggest that corporate bonds are positively related to the excess return on tea whereas Treasury bonds are negatively related with the excess return on tea. In contrast, stocks, gold or silver do not show any significant relationship with the excess return on tea. Furthermore, the constant term of all these regressions is not significant and hence one can conclude that it is not statistically significant to consider tea as a separate asset in the portfolio of an average investor.

[Insert Table 3.11 about here]

3.8. Conclusion

This study investigates the fascinating question of why tea has not yet developed into an investable commodity in the financial markets. First, it provides an overview about this mostly unknown and less researched oldest tea market. I explored the Sri Lankan tea market and provided information about its historical evolution and the current scenario. Since there is no derivative product to mitigate the price risk faced by the tea market participants in Sri Lanka, this study evaluates the viability of introducing a futures contract on tea. Finally, it studies whether a futures contract on tea can attract the interest of investors by providing diversification benefits into their portfolios.

According to the findings of this study, introducing a futures contract on tea is not an impossible task, but it is challenging given the existing structure of the tea market. The existing cash market of tea and the risks faced by tea market participants favourably support the need for a futures contract on tea. Such a contract would be highly beneficial for market participants in Sri Lanka as well as other tea producing countries in mitigating their price risk, as there is no tea futures contract in the world at present.

However, there is a major role to be played by policy makers to create the required infrastructure for a futures market. First, tea market regulators all over the world should agree on a common grading system for tea. Second, policy makers and regulators in Sri Lanka should create a supportive regulatory environment for establishing a futures contract. Third, tea market regulators need to understand the utmost importance of moving forward with the tea auction by automating the auction process. An automated auction will provide easy access to international tea buyers and hence able to globalize this market and attract speculators more easily. Finally, the government, tea market regulators and even the academics in Sri Lanka, have a responsibility to enhance the awareness of tea market participants and other investors regarding the uses of a futures contract.

Finally, I identified that adding tea would shift the mean-variance efficient frontier from the GMVP point. The results reveal that tea would diversify the risk involved in the GMVP and an equally weighted portfolio. In contrary, the Mean-Variance Spanning test suggests that tea does not act as a statistically significant asset in a portfolio. Therefore, attracting investors to financialize a futures market on tea presents a challenge.

Further research is required to develop a suitable grading system, to design a proper electronic trading platform for tea and to decide the optimal contract design for a futures contract on tea, if it is to be introduced. I believe these empirical findings and the knowledge gathered would essentially pave the way for financializing the tea market by linking this separated tea market with the financial market.

In addition, the methodology used in this study can be applied to identify the feasibility of introducing a futures contract on any other commodities as well. Any commodity with a significant price volatility and a clear grading system can be considered as possible new commodities for futures contracts.

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Appendix 1

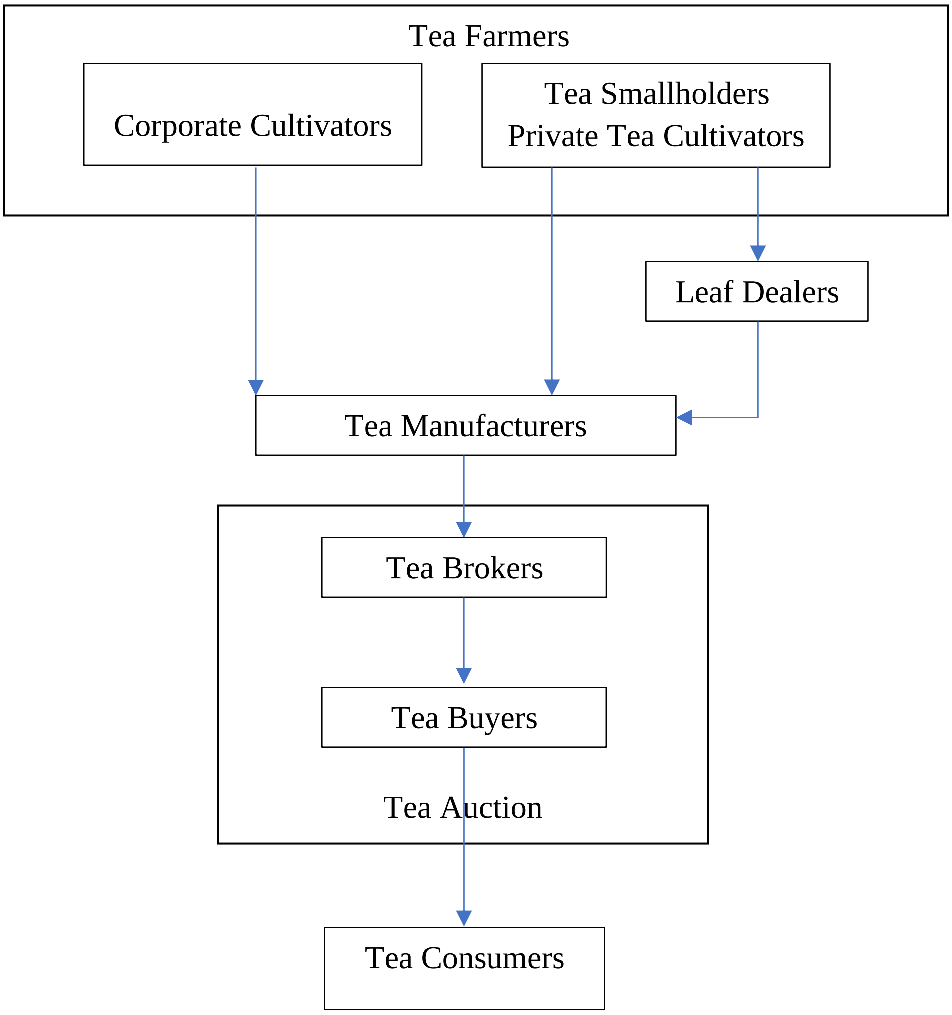

Figure 3.1: Value chain of the tea market in Sri Lanka
Source: Authors' Work

Note: This figure depicts the value chain of tea market in Sri Lanka. There are two types of tea farmers: corporate cultivators and private cultivators/ tea smallholders. Corporate cultivators have their own tea manufacturing facilities whereas only some private tea cultivators have their own tea factories. Private tea cultivators and tea smallholders without tea manufacturing facilities either sell their tea green leaves directly or via leaf dealers to the nearby tea factory. Thereafter, produced tea is sold in the tea auction via tea brokers representing both buyers and tea manufacturers. There are two types of tea buyers: export buyers (who buy tea for export purposes) and local buyers (who buy tea to sell in the local market). Finally, well-packed and labelled packet of tea reaches the tea consumers for final consumption.

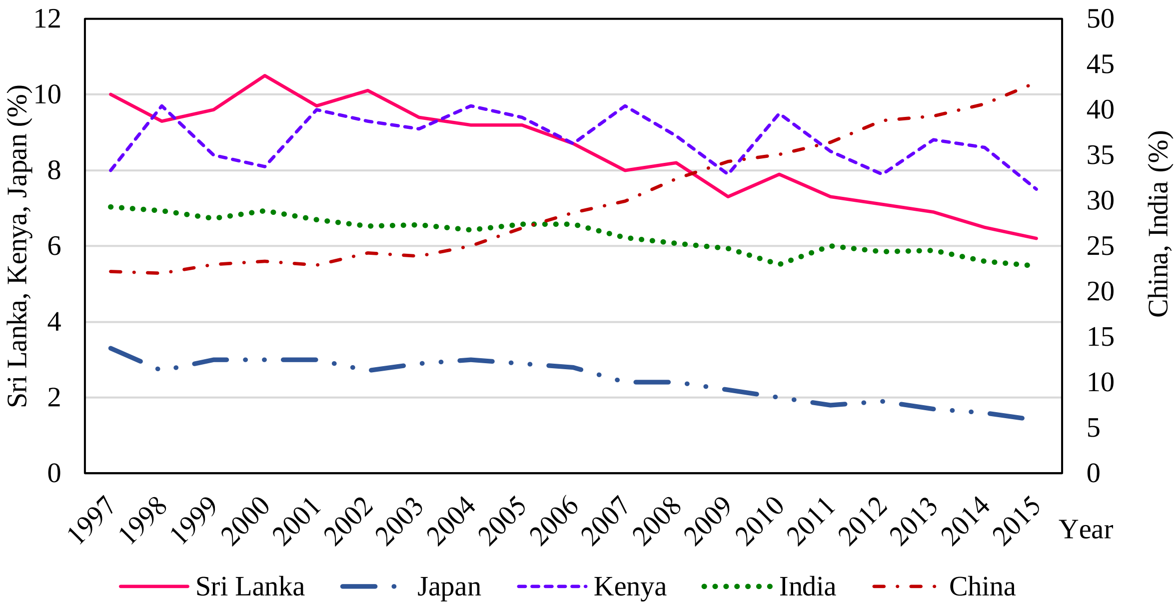

Figure 3.2: World tea production (in percentage)
Source: Statistical Bulletin 2015, Sri Lanka Tea Board

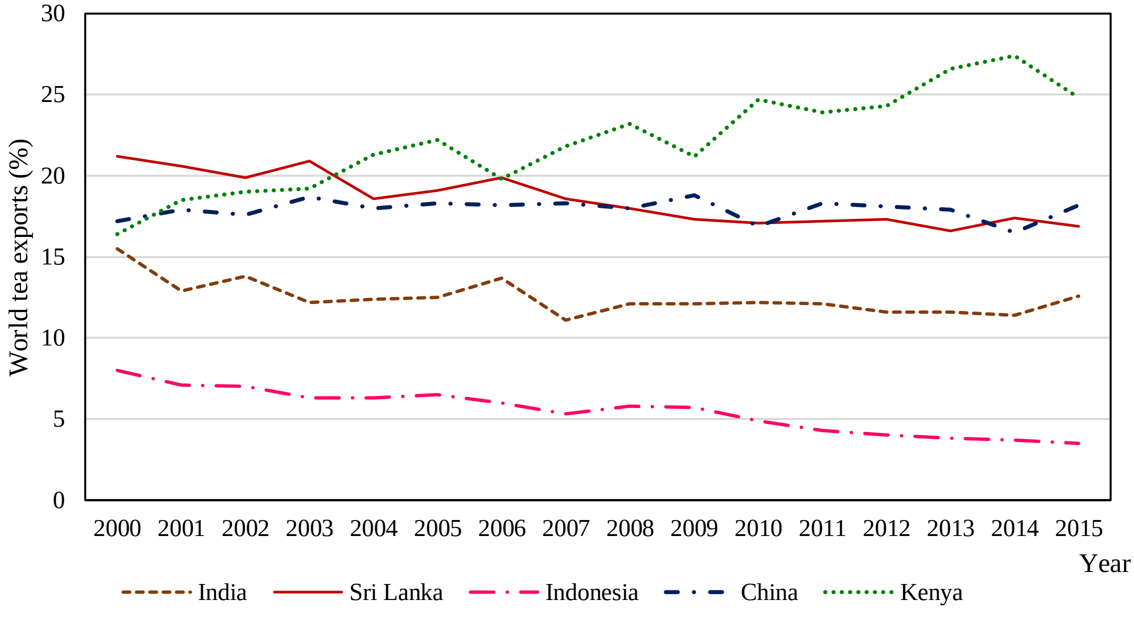

Figure 3.3: World tea export (in percentage)
Source: Statistical Bulletin 2015, Sri Lanka Tea Board

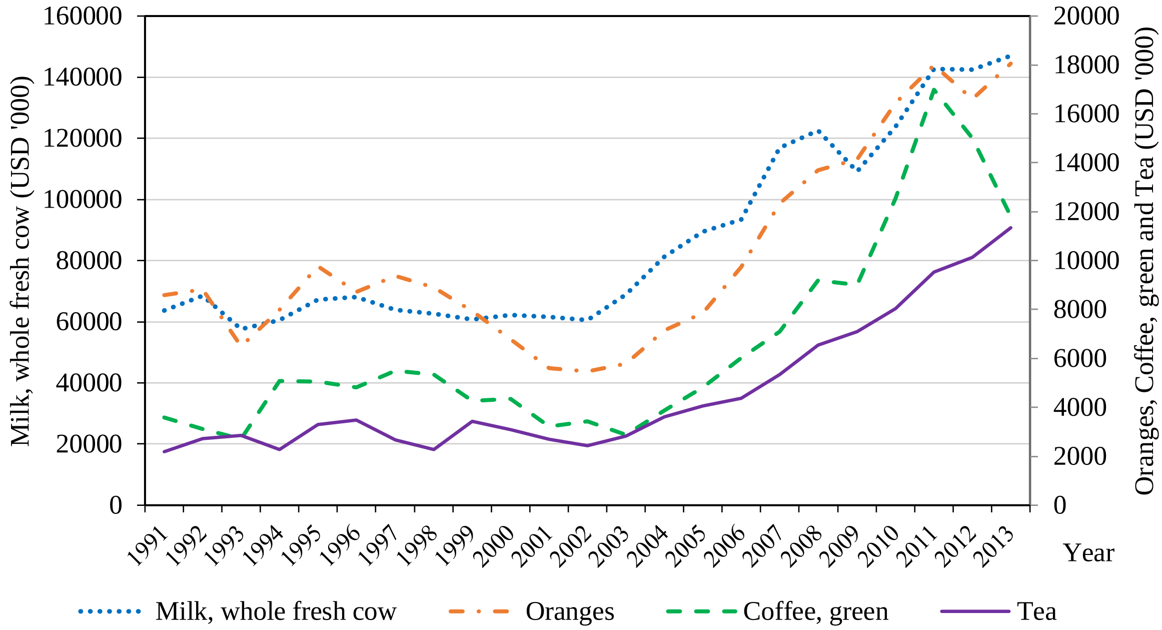

Figure 3 4: World production values of coffee, orange juice, milk and tea
Source: Food and Agriculture Organization Database

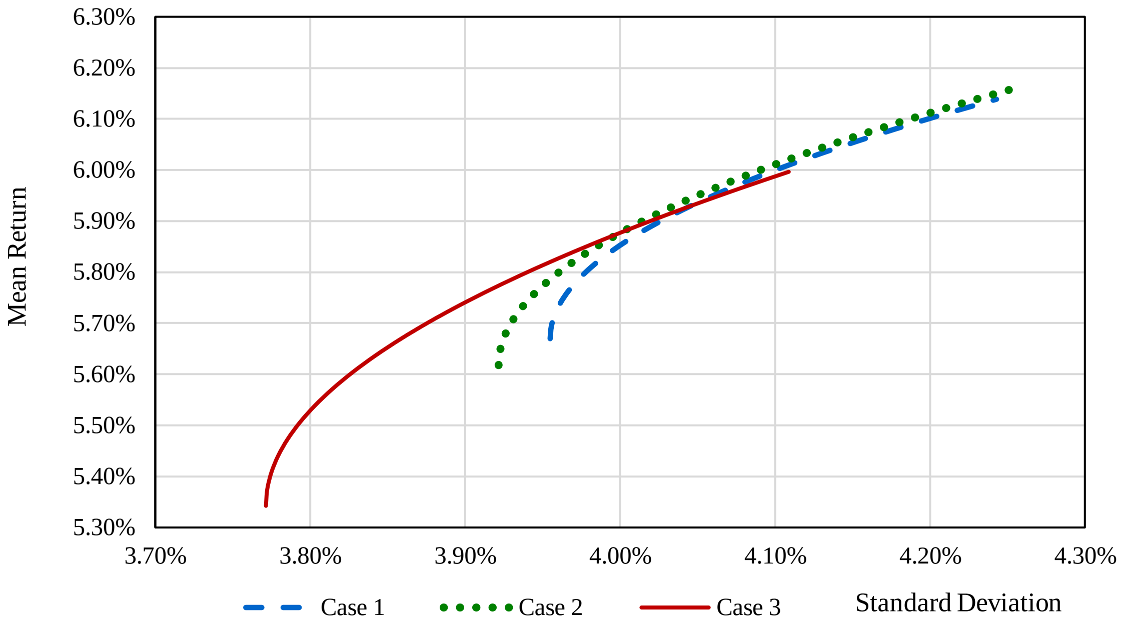

Figure 3.5: Efficient frontier under three scenarios
Source: Authors' Work

Note: Case 1 includes a portfolio of stocks, corporate bonds and treasury bonds. Case 2 includes a portfolio of stocks, corporate bonds, treasury bonds, gold and silver. Case 3 includes a portfolio of stocks, corporate bonds, treasury bonds, gold, silver and tea. This graph shows the efficient frontiers of these three portfolios. The X axis shows the standard deviation of the portfolios and the Y axis shows the portfolio returns.

Appendix 2

Table 3.1: List of factors determining the success of a futures contract

This table summarizes the characteristics of the cash market, commodity and the futures market that should exist in order to introduce a futures contract successfully. These factors are identified as relevant in below mentioned existing literature. This list acts as a checklist to decide the appropriateness of tea as a commodity for a futures contract.

Category	Characteristic	Literature
Cash	Volatility of cash prices	Bekkerman and Tejeda (2017); Black (1986); Tashjian and Weissman (1995); Webb (2015)
Cash	Size of the market	Black (1986); Bekkerman and Tejeda (2017); Carlton (1984); Tashjian and Weissman (1995)
Cash	Activeness of the market	Bekkerman and Tejeda (2017); Brorsen and Fofana (2001)
Cash	Degree of vertical integration	Bekkerman and Tejeda (2017); Brorsen and Fofana (2001)
Cash	Degree of buyer concentration	Bekkerman and Tejeda (2017); Brorsen and Fofana (2001)
Commodity	Homogeneity	Atkin (1989); Bekkerman and Tejeda (2017); Brorsen and Fofana (2001)
Futures	Availability of cross-hedging	Bekkerman and Tejeda (2017); Black (1986); Webb (2015)
Futures	Liquidity cost of cross-hedging	Black (1986); Webb (2015)
Futures	Public order flow	Bergford (2007); Webb (2015)
Futures	Timing	Cuny (1993); Economides and Siow (1985); Webb (2015)
Futures	Nature of the trading platform	Ates and Wang (2005); Frank and Garcia (2009); Pirrong (1996); Shah and Brorsen (2011); Tse and Zabotina (2001)
Futures	Contract design	Gray (1966); Johnston and McConnell (1989); Webb (2015)
Futures	Ability to attract speculators	Gray (1966); Till (2015); Webb (2015)
Futures	Need for hedging	Cuny (1993); Gray (1966); Johnston and McConnell (1989); Silber (1981); Till (2015); Webb (2015)
Futures	Public policy support	Till (2015)

Source: Author’s work

Table 3.2: Grades of Orthodox black tea

This table summarizes the grading system of Orthodox black tea adopted in Sri Lanka. This is a summary of the major grades of black tea produced in Sri Lanka. There are two main categories: Whole leaf grades and Broken leaf grades.

Type of the Leaf	**Grade Name**	**Nomenclature**
Whole leaf grades	SFTGFOP	Special Finest Tippy Golden Flowery Orange Pekoe
	FTGFOP	Finest Tippy Golden Flowery Orange Pekoe
	TGFOP	Tippy Golden Flowery Orange Pekoe
	GFOP	Golden Flowery Orange Pekoe
	FOP	Flowery Orange Pekoe
	OPA	Orange Pekoe A
	OP1	Orange Pekoe One
	OP	Orange Pekoe
	FP	Flowery Pekoe
	P	Pekoe
	PS	Pekoe Souchong
	S	Souchong
Broken leaf grades	TGFBOP	Tippy Golden Flowery Broken Orange Pekoe
	GFBOP	Golden Flowery Broken Orange Pekoe
	GBOP	Golden Broken Orange Pekoe
	FBOP	Flowery Broken Orange Pekoe
	BOP1	Broken Orange Pekoe One
	BOP1A	Broken Orange Pekoe One A
	BOP	Broken Orange Pekoe
	BP1	Broken Pekoe One
	BP	Broken Pekoe
	BPS	Broken Pekoe Souchong
Fannings	BOPF	Broken Orange Pekoe Fannings
	GOF	Golden Orange Fannings
	OF	Orange Fannings
	PF1	Pekoe Fannings One
	PF	Pekoe Fannings
Dust	PD	Pekoe Dust
	D1	Dust One
	D	Dust

Source: Hall, N. (2000). *The Tea Industry*. Cambridge, England: Woodhead Publishing Limited.

Table 3.3: Risks in the tea value chain of Sri Lanka

This table summarizes different risks faced by the tea market participants in Sri Lanka. The detailed discussion of these risks are available in Section 3.4.3. This list is a compilation based on the analysis of the information and findings in this study.

Participant	Risks Faced
Corporate Cultivators	• Changing weather conditions • Uncertainty about the tea prices • Perishability nature of the tea • Uncertainty about the lease on land • Lack of skilled labour • Rising cost of production due to increasing wage rate • High cost to exit
Private Cultivators/ Tea Smallholders	• Changing weather conditions • Uncertainty about the tea prices • No guaranteed price for tea green leaves • Perishability nature of the tea • Lack of financial resources • High cost to exit
Tea Manufacturers	• Uncertainty about the tea prices • High cost to exit • Lack of skilled labour • Rising cost of production due to increasing wage rate
Tea Exporters	• Default risk on tea consignments sold • Lack of short term finance due to extending the credit policy to attract exporters

Source: Author's work

Table 3.4: List of commodities included in the Bloomberg Agriculture Total Return Index

This table lists different agricultural indices included in the Bloomberg Agricultural Total Return Index published by the Bloomberg database. This study use this index to represent the overall return on the agriculture markets. The daily values of these indices are obtained from the Bloomberg for the period from January 1991 to October 2017.

Bloomberg Ticker	Index Name
BCOMBOTR	Bloomberg Soybean Oil Subindex Total Return
BCOMCCTR	Bloomberg Cocoa Subindex Total Return
BCOMCNTR	Bloomberg Corn Subindex Total Return
BCOMCTTR	Bloomberg Cotton Subindex Total Return
BCOMFC	Bloomberg Feeder Cattle Subindex
BCOMKCTR	Bloomberg Coffee Subindex Total Return
BCOMKW	Bloomberg Kansas Wheat Subindex
BCOMLCTR	Bloomberg Live Cattle Subindex Total Return
BCOMLHTR	Bloomberg Lean Hogs Subindex Total Return
BCOMOJ	Bloomberg Orange Juice Subindex
BCOMSBTR	Bloomberg Sugar Subindex Total Return
BCOMSM	Bloomberg Soymeal Subindex
BCOMSYTR	Bloomberg Soybean Subindex Total Return
BCOMWHTR	Bloomberg Wheat Subindex Total Return

Source: Bloomberg Database

Table 3.5: Annualized volatilities of agricultural commodities

This table summarizes annualized volatilities of agricultural commodities listed in Table 3.4 including tea. Tea prices reported at the Colombo Tea Auction are obtained from the Global Economic Monitor database of World Bank and the prices of all other agricultural commodities are obtained from the Bloomberg. The data covers the period from January 1991 to October 2017. The rank of tea indicates the rank of tea when the yearly volatilities are arranged in the descending order.

Year	**Tea**	**Rank of Tea**	Soybean Oil	Cocoa	Corn	Cotton	Feeder Cattle	Coffee	Kansas Wheat	Live Cattle	Lean Hogs	Orange Juice	Sugar	Soymeal	Soybean	Wheat
1991	**22%**	**3**	20%	27%	21%	21%	9%	18%	14%	10%	17%	40%	27%	16%	17%	17%
1992	**33%**	**1**	17%	22%	18%	23%	10%	32%	20%	8%	12%	24%	20%	9%	14%	20%
1993	**21%**	**5**	18%	19%	13%	16%	7%	42%	17%	7%	22%	49%	34%	16%	14%	17%
1994	**19%**	**5**	19%	34%	17%	24%	12%	58%	17%	15%	27%	27%	17%	12%	15%	16%
1995	**32%**	**2**	11%	18%	10%	26%	13%	40%	25%	14%	14%	21%	19%	12%	9%	21%
1996	**26%**	**6**	15%	7%	29%	13%	14%	46%	31%	16%	23%	27%	17%	20%	19%	30%
1997	**12%**	**10**	17%	28%	24%	9%	11%	63%	34%	9%	11%	26%	13%	30%	26%	31%
1998	**15%**	**10**	19%	13%	23%	20%	16%	33%	20%	15%	32%	40%	25%	25%	20%	22%
1999	**24%**	**7**	29%	34%	14%	14%	9%	49%	20%	7%	39%	40%	45%	17%	20%	23%
2000	**16%**	**10**	23%	19%	25%	31%	6%	21%	16%	9%	22%	20%	38%	25%	22%	17%
2001	**16%**	**9**	30%	45%	20%	36%	10%	18%	17%	14%	15%	21%	36%	22%	21%	20%
2002	**17%**	**10**	21%	29%	15%	25%	12%	39%	31%	11%	45%	20%	35%	11%	12%	26%
2003	**12%**	**10**	25%	51%	25%	30%	21%	30%	21%	30%	24%	15%	32%	33%	29%	25%
2004	**19%**	**8**	43%	34%	33%	38%	16%	46%	15%	14%	18%	34%	12%	35%	39%	18%
2005	**16%**	**11**	25%	21%	23%	27%	11%	26%	19%	11%	18%	26%	21%	31%	29%	24%
2006	**16%**	**8**	21%	16%	27%	13%	15%	21%	21%	18%	23%	21%	38%	20%	20%	19%
2007	**16%**	**11**	12%	25%	30%	23%	13%	20%	36%	10%	27%	33%	23%	28%	18%	37%
2008	**28%**	**11**	57%	50%	47%	41%	16%	41%	43%	16%	32%	33%	42%	46%	49%	42%
2009	**30%**	**6**	22%	30%	33%	26%	9%	29%	34%	9%	26%	39%	36%	27%	25%	38%
2010	**13%**	**12**	27%	24%	36%	37%	15%	28%	40%	8%	19%	19%	63%	24%	26%	45%
2011	**11%**	**12**	20%	42%	38%	39%	19%	38%	44%	17%	23%	30%	34%	30%	27%	44%
2012	**21%**	**9**	19%	24%	39%	28%	16%	20%	24%	11%	17%	47%	27%	33%	30%	25%
2013	**12%**	**10**	15%	17%	15%	23%	10%	11%	21%	5%	16%	30%	13%	22%	19%	17%
2014	**10%**	**15**	23%	17%	33%	24%	13%	46%	31%	12%	28%	19%	18%	34%	26%	36%
2015	**13%**	**13**	22%	23%	25%	17%	24%	20%	35%	19%	27%	38%	31%	24%	22%	40%
2016	**13%**	**13**	18%	25%	24%	25%	21%	29%	16%	17%	41%	37%	31%	35%	24%	19%
2017	**13%**	**10**	15%	30%	10%	13%	19%	22%	31%	19%	23%	28%	24%	19%	16%	30%

Source: Author’s work

Table 3.6: Cross correlations between tea and coffee prices

This table summarizes the cross-correlations between world average tea prices, tea prices at the Colombo Tea Auction, coffee Arabica prices, coffee Robusta prices and composite coffee prices. The Panel A includes price data obtained from the Global Economic Monitor Database and the Panel B obtained Composite Coffee price index data collected from the International Coffee Organization. The data covers the period from January 1991 to October 2017.

Panel A	Coffee Arabica	Coffee Robusta	World Average Tea	Tea (Colombo)
Coffee Arabica	1			
Coffee Robusta	0.7142	1		
World Average Tea	0.0997	0.0683	1	
Tea (Colombo)	0.0589	-0.0082	0.3941	1

Panel B	World Average Tea	Tea (Colombo)	Coffee Composite
World Average Tea	1		
Tea (Colombo)	0.3941	1	
Coffee Composite	0.0879	0.0491	1

Source: Author’s work

Table 3.7: Determinants of the success of a futures contract

This table summarizes the quality of the Sri Lankan tea market in meeting the success criteria of a futures contract. The detailed discussion related to this table is provided in Section 3.6. The quality of these criteria is decided solely based on the findings and the discussion in this study.

Success criteria	Quality of the tea market
Cash price volatility	Sufficient
Cash market size	High
Cash market activeness	High
Product Homogeneity	Need to standardize
Vertical integration	High - Not supportive
Buyer concentration	High - Not supportive
Availability of cross-hedging	Poor
Need for hedging	High
Interest of speculators	Poor but can attract
Public order flow	High
Trading platform	Need to automate

Source: Author’s work

Table 3.8: Descriptive statistics and correlations among agricultural commodities

This table summarizes the mean return, standard deviation, Sharpe ratios of commodities along with their correlation values with tea. The descriptive statistics are calculated based on monthly returns from January 1991 to October 2017. The mean returns and standard deviations are annualized. Sharpe ratio is the ratio of excess return to standard deviation. The risk-free rate is 90-day US Treasury Bill rate.

Variable	Observations	Mean	Standard Deviation	Sharpe Ratio	Correlation with Tea
Tea	322	1.93%	16.81%	-0.0391	1.0000
Cocoa	322	-2.72%	28.58%	-0.1857	0.1013
Coffee	322	-5.25%	35.84%	-0.2187	0.1085
Corn	322	-6.39%	26.12%	-0.3436	0.0184
Cotton	322	-2.92%	26.28%	-0.2097	0.1105
Feeder Cattle	322	1.89%	14.44%	-0.0480	0.1015
Kansas Wheat	322	-4.88%	27.05%	-0.2760	0.0786
Lean Hogs	322	-7.21%	25.12%	-0.3901	-0.0227
Live Cattle	322	1.58%	13.86%	-0.0728	0.0704
Orange Juice	322	-5.10%	31.02%	-0.2478	0.0631
Soybean	322	5.50%	23.73%	0.1226	0.0975
Soybean Oil	322	-0.57%	24.08%	-0.1310	0.0941
Soymeal	322	7.30%	25.70%	0.1833	0.0880
Sugar	322	2.40%	30.61%	-0.0062	0.0974
Wheat	322	-7.70%	27.96%	-0.3678	0.0760

Source: Author’s work

Table 3.9: Descriptive statistics and correlations between investment assets

This table summarizes the mean return, standard deviation, Sharpe ratios and correlation values with tea. The descriptive statistics are calculated based on monthly returns from January 1991 to October 2017. The monthly mean returns and standard deviations are annualized. Sharpe ratio is the ratio of excess return to standard deviation. S&P 500 index represents the equity investment. Bloomberg Barclays US Corporate Bond index and Bloomberg Barclays US Treasury Bonds Index represent bonds. Gold and silver price indices in USD are obtained from the Bloomberg. The risk-free rate is 90-day US Treasury Bill rate.

Variable	Observations	Mean	Standard Deviation	Sharpe Ratio	Correlation with Tea
Tea	323	1.96%	16.78%	-0.0375	1.0000
S&P 500	323	7.84%	14.20%	0.3698	0.0793
Corporate Bonds	323	6.43%	5.34%	0.7197	0.0564
Treasury Bonds	323	5.38%	4.35%	0.6405	-0.1032
Gold	323	5.36%	15.97%	0.1736	0.0502
Silver	323	7.23%	30.03%	0.1545	0.0802
Treasury Bills	323	2.59%	0.64%	0.0000	-0.0183

Source: Author’s work

Table 3.10: Portfolio performance under different scenarios

This table summarizes the investment proportions, annualized mean returns, annualized standard deviations and coefficient of variations of the Global Minimum Variance Portfolio (GMVP), Tangent Portfolio and an equally weighted portfolio under three cases. Case 1 includes a portfolio of stocks, corporate bonds and treasury bonds. Case 2 includes a portfolio of stocks, corporate bonds, treasury bonds, gold and silver. Case 3 includes a portfolio of stocks, corporate bonds, treasury bonds, gold, silver and tea.

Asset	Case 1			Case 2			Case 3		
	GMVP	Tangent Portfolio	Equally Weighted	GMVP	Tangent Portfolio	Equally Weighted	GMVP	Tangent Portfolio	Equally Weighted
S&P 500	12%	11%	34%	12%	11%	20%	11%	11%	17%
Corporate Bonds	-5%	37%	33%	-8%	37%	20%	-12%	39%	17%
Treasury Bonds	92%	52%	33%	93%	54%	20%	93%	53%	17%
Gold	-	-	-	1%	-3%	20%	1%	-3%	17%
Silver	-	-	-	2%	2%	20%	1%	2%	17%
Tea	-	-	-	-	-	-	7%	-1%	17%
Mean Return	5.6698%	6.1385%	2.5515%	5.6178%	6.1615%	5.8734%	5.3091%	6.2279%	5.2163%
Standard Deviation	0.0452%	0.0520%	0.0967%	0.0444%	0.0523%	0.2499%	0.0405%	0.0541%	0.2072%
Coefficient of Variation	0.7963%	0.8466%	3.7900%	0.7903%	0.8489%	4.2550%	0.7638%	0.8692%	3.9714%

Source: Author's work

Table 3.11: Mean – variance spanning test results

This table summarizes the results of the Mean-Variance Spanning test. The dependent variable of all five regression models is the excess return on tea. The table presents the coefficient of each independent variable and its standard deviation (SE) under each model in the columns. The data covers the period from January 1991 to October 2017. *, ** and *** indicate the significance at 1%, 5% and 10% level, respectively.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	SE	β	SE	β	SE	B	SE	β	SE
S&P 500	0.0946	0.0818	0.0814	0.0812	-0.0415	0.0823	-0.0404	0.0814	-0.0442	0.0826
Corporate Bonds	-	-	0.1415	0.2098	0.8696*	0.3007	0.8472*	0.2860	0.8458*	0.2891
Treasury Bonds	-	-	-	-	-1.1648*	0.3941	-1.1708*	0.3899	-1.1531*	0.3987
Gold	-	-	-	-	-	-	0.0520	0.0607	0.0313	0.1025
Silver	-	-	-	-	-	-	-	-	0.0142	0.0509
Constant	-0.0009	0.0028	-0.0013	0.0028	-0.0004	0.0028	-0.0005	0.0028	-0.0005	0.0028

Source: Author's work

Chapter Four

Commodity Futures Hedge Ratios: A Meta-Analysis

4.1. Introduction

Over past decades, the use of financial derivatives has increased exponentially and thereby the importance of derivative accounting as well. A derivative is a financial asset designed to manage a specific risk exposure. The price of a derivative is derived based on the price of the underlying asset of the contract. Despite the fact that derivatives are designed to hedge a risk exposure, firms can also use derivatives to earn a speculative profit by increasing the exposure to a specific risk.

World-renowned investor, Warren Buffett, once stated that derivatives are "financial weapons of mass destruction" in the annual report of Berkshire Hathaway Inc. (2002). The corporate scandals such as United California Bank of Basel (1970), Codelco (1993), Metallgescellschaft (1993), Sumitomo Corporation (1996), China Aviation Oil (2004) and Amaranth Advisors (2006) provide evidence that, if not used with a proper knowledge, derivatives on commodities can destroy the value of a firm in any country at any time.[1] Therefore, it is vital for the users of derivatives to clearly understand the intended use of derivatives and differentiate their position between hedging and speculation. Due to this complexity nature of financial derivatives, the accounting for derivatives has evolved continuously in the past and will continue to do so in the future.

At present, there are two financial reporting guidelines for derivatives internationally. In 2017, Financial Accounting Standards Board (FASB) issued Accounting Standards Update

[1] United California Bank of Basel trading cocoa futures in 1970 in Switzerland, Codelco trading copper, silver and gold futures in 1993 in Chile, Metallgesellschaft trading oil futures in 1993 in Germany, Sumitomo Corporation trading copper futures in 1996 in Japan, China Aviation Oil trading oil futures and options in 2004 in China and Amaranth Advisors trading natural gas futures in 2006 in United States are examples of highly publicized derivative trading scandals related to commodity markets.

(ASU) 2017-12 for Derivatives and Hedging (Topic 815): Targeted Improvements to Accounting for Hedging Activities. Concurrently, International Accounting Standards Board (IASB) has issued IFRS 9: Financial Instruments in 2014.[2] FASB issues accounting standards applicable for the United States whereas the rest of the world adopts accounting standards issued by the IASB.

According to ASU 2017-12, the hedging instrument is expected to be highly effective in offsetting changes in the fair value or cash flows of the hedged item during the period that the hedge is designated. This high effectiveness requires to be between 80 percent and 125 percent or to be between 0.8 and 1.25. If a firm fails to achieve this threshold level, hedge accounting is not applicable. In contrast, IFRS 9 requires the optimal hedge ratio to remain appropriate to the risk management strategy of the firm and emphasizes maintaining an economic relationship between the hedged item and the hedging instrument rather than emphasizing a cut-off level.

The real question is why firms prefer to be qualified for hedge accounting and what the benefits of applying hedge accounting are. If a firm qualifies for hedge accounting, derivative gains or losses are deferred recognizing in the income statement until the contract is closed. In contrast, if a firm does not qualify for hedge accounting (considered as speculative trading), derivative gains or losses are recognized in the income statement of each period when the gains or losses arise. Thus, not being qualified for hedge accounting may increase the earnings volatility of a company.

The existing accounting literature provides evidence for the use of derivatives and the benefits of hedge accounting. According to Barton (2001), hedging reduces earnings volatility, hedge accounting acts as a substitute for accruals management and as a tool for earnings

[2] The information about the IFRS 9 and ASU 2017-12 are obtained from the reports issued by the PricewaterhouseCoopers (PwC) (2017; 2018; 2019) and the Ernst & Young (EY) (2019).

management. However, after the implementation of SFAS 133, hedging became less useful as a tool for smoothing earnings (Choi, Mao and Upadhyay, 2015; Kilic et al., 2013). Furthermore, previous studies have found the use of derivatives for hedging reduces the cost of equity of the firm (Gay, Lin and Smith, 2011) and reduces the cost of debt as well (Chen and King, 2014). However, the debate regarding the informativeness of derivative accounting is still unresolved. Dadalt, Gay and Nam (2002) conclude that derivative accounting can reduce the information asymmetry of a firm whereas Dewally and Shao (2013) and Lin and Lin (2012) find the firms using derivatives experience an increase in the level of information asymmetry.

The differences then prevailing in accounting standards aggravated the issue in the derivative trading scandal in Metallgescellschaft. MG Refining and Marketing Inc. (MGRM) is a US subsidiary of Metallgesellschaft AG, a German conglomerate, and was in charge of refining and marketing petroleum products in the United States. In December 1993, the MGRM revealed an approximately USD 1.5 billion loss in their derivative based trading strategy on oil. According to the US hedge accounting practices, MGRM could offset the unrealized loss on their futures contracts with the unrealized gain on their forward contracts. Hence, under US hedge accounting practices, MGRM reported a profit in their financial statements for the year 1993. In contrast, German accounting principles on hedging, allowed recognition to only unrealized losses on the financial statements but did not allow recognition of the unrealized gain on hedging. Therefore, MGRM reported a massive loss on derivative-related trading strategy on oil in the consolidated financial statements of Metallgesellschaft.[3] This case accentuated the necessity to have proper guidelines to determine the fine line between hedging and speculation in derivative trading. In contrast to that, these highly publicized corporate scandals pressured accounting standard setters to revise their accounting policies (Barnes, 2001).

[3] See Edwards and Canter (1995) for further details.

The existing literature on derivatives has studied several questions related to the hedging effectiveness of derivatives. First, there are studies discussing the alternative techniques that can be used to estimate the hedging effectiveness and/or introducing new methods to estimate the hedging effectiveness (Finnerty and Grant, 2002; Frestad and Beisland, 2015; Hailer and Rump, 2005; Kawaller and Koch, 2000). Second, these studies argue that the 'highly effective' screening mechanism based on the threshold levels in FAS 133 and IAS 39 is not an effective way to delineate the fine line between hedging and speculation (Frestad and Beisland, 2015; Hailer and Rump, 2005; Kawaller and Koch, 2000). Third, these studies identify the limitation of using the regression model introduced by Ederington (1979) and Johnson (1960) to measure the hedging effectiveness.

Surprisingly, there is hardly any empirical evidence to illustrate how accounting standard setters justify selection of these threshold levels of hedging effectiveness. Since the decision regarding being qualified for hedge accounting is crucial to a firm, it is important that this threshold level be justifiable. Therefore, this study contributes to the existing literature by providing academic evidence regarding the appropriate optimal hedge ratio and the level of hedge effectiveness using meta-analysis methodology. Furthermore, it examines whether there is a selection bias when reporting optimal hedge ratios related to commodity-based hedging. Finally, it investigates the factors determining the heterogeneity in the reported hedge ratios in different markets for different commodities in different time periods. I believe the findings of this study will provide valuable insights for the policy makers in their ongoing efforts of improving the derivative accounting standards.

The rest of the chapter is organized as follows. Section 4.2 provides a brief explanation about the evolution of derivative accounting. Thereafter, Section 4.3 summarizes the literature on the alternative theories of hedging and evidence on possible factors affecting the optimal hedge ratio. In Section 4.4, this study discusses the research design, sample of data and characteristics of data. Section 4.5 introduces the meta-analysis methodology of testing the publication bias and presenting the results thereof. Section 4.6 defines the variables identified as potential determinants of heterogeneity in hedge ratios in commodity markets. Section 4.7 introduces the meta-regression methodology and discusses the meta-regression results of each sub-sample. Finally, Section 4.8 summarizes the findings and concludes.

4.2. Evolution of Derivative Accounting

FASB issues Generally Accepted Accounting Principles (GAAP) adopted in United States whereas IASB issues International Financial Reporting Standards (IFRS) adopted by approximately 120 nations in the world.[4] Both FASB and IASB have issued their own reporting standards on derivative accounting and have updated them continuously during the past decades.

FASB has issued several accounting standards on derivatives at early stages.[5] FAS 52: Foreign Currency Translation in 1981 and FAS 80: Accounting for Futures Contracts in 1984. FAS 52 and FAS 80 did not cover contracts like interest rate derivatives and options. Therefore, FASB then introduced FAS 105, FAS 107 and FAS 119 in 1990, 1991 and 1994, respectively in order to cater to this problem of limited scope in previous standards.[6] These new accounting standards focused in the main on improving the disclosure requirements relating to derivative accounting. At that time, none of these accounting standards were applicable for commodity derivatives. Therefore, FAS 80, FAS 105 and FAS 119 were then superseded by FAS 133: Accounting for Derivative Instruments and Hedging Activities in 1998.

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[4] This information is obtained from https://www.ifrs.com/ifrs_faqs.html#q3.

[5] For details about the accounting standards issued by the FASB, please refer to https://www.fasb.org/home.

[6] FAS 105: Disclosure of Information about Financial Instruments with Off-Balance-Sheet Risk and Financial Instruments with Concentrations of Credit Risk, FAS 107: Disclosures about Fair Value of Financial Instruments and FAS 119: Disclosure about Derivative Financial Instruments and Fair Value of Financial Instruments.

The two important accounting standards on derivative accounting issued by the FASB are FAS 133 and Accounting Standards Update (ASU) 2017-12. FAS 133: Accounting for Derivative Instruments and Hedging Activities standard was issued in 1998. FAS 133 was the first comprehensive standard standardizing accounting practices on derivatives. To qualify for hedge accounting under FAS 133, the hedging relationship is expected to be 'highly effective'. This effectiveness should be measured at the beginning of the hedge and on an on-going basis whenever financial statements are reported, or at least every three months. Contrarily, there is no proper guidance in the FAS 133 regarding the method measuring the effectiveness of a hedge. The only guideline provided by the accounting standard is that the hedging effectiveness should be in the range of 80% to 125%.

Thereafter, FASB recently issued Accounting Standards Update (ASU) 2017-12 in 2017.[7] The ASU 2017-12 did not change the hedge effectiveness threshold level of 80% to 125%. Nevertheless, these new amendments have changed the effectiveness measurement methodologies to better align them with the risk management strategy of a company. To simplify the reporting, these amendments removed the need to estimate and report hedge ineffectiveness. Furthermore, it now allows a company to use a qualitative approach to measure the subsequent effectiveness of a hedge after being designated under hedge accounting. By introducing these changes, FASB intended to simplify hedge accounting, reduce the cost and complexity of hedge accounting.

Conversely, IASB has also issued two major accounting standards on derivatives: IAS 39: Financial Instruments: Recognition and Measurement issued in 2003 and then it was superseded by IFRS 9: Financial Instruments in 2014.[8] IAS 39 also required the hedge

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[7] Please refer to https://www.fasb.org/jsp/FASB/FASBContent_C/GeneralContentDisplay&cid=1176169280252 for more details.

[8] For more details about the accounting standards issued by the IFRS refer to https://www.iasplus.com/en/standards/ias and https://www.ifrs.org/issued-standards/list-of-standards/.

effectiveness to be in the range of 80% to 125% but did not specify the method of calculating hedge effectiveness. However, IAS 39 was a complex standard and the companies had to incur considerable consultation fees in applying this standard to their businesses. In order to reduce the level of complexity, and to improve the efficient application of these standards, IASB revised IAS 39 and replaced it with IFRS 9. This new standard now requires the hedge ratio to remain appropriate to the risk management strategy of the firm instead of achieving a threshold level of hedging effectiveness. It further removes the need to conduct retrospective effectiveness tests. However, under IFRS 9 unlike in IAS 39, firms cannot voluntarily reverse their decision to apply hedge accounting when they are eligible for hedge accounting.

Both these accounting standard regimes issued by FASB and IASB remain silent regarding the best method to measure hedge effectiveness. Previous academic literature discusses different methods used to measure hedging effectiveness (Finnerty and Grant, 2002; Frestad and Beisland, 2015; Hailer and Rump, 2005; Kawaller and Koch, 2000). Among all the widely adopted methods currently in practice are the Dollar offset method[9] and regression analysis. Despite being easy to calculate and simple to understand, Dollar offset method fails to achieve the threshold level of effectiveness during periods of low-price volatility. The other widely adopted statistical method is the regression technique in which it regresses the spot prices of the hedged item on the prices of the derivative. The slope of this regression is the optimal hedge ratio between the hedged item and the derivative, and the R squared shows the effectiveness of hedging. The findings of the regression analysis would only be reliable if the hedger has used the appropriate regression model and the appropriate data (Kawaller and Koch, 2000).

[9] The Dollar offset method compares the change in fair value or present value of cash flows of the hedging instrument to the change in the fair value or present value of cash flows of the hedged item. The dollar-offset method can be used to measure the prospective and/or the retrospective effectiveness of hedging.

4.3. Literature Review

As per the accounting standards mentioned above, a hedge should meet the threshold level of hedging effectiveness in order to apply hedge accounting. The empirical evidence on futures hedging in commodity markets is voluminous.[10] The previous literature on derivatives has widely studied the method of determining the optimal hedge ratio and hedging effectiveness and the factors affecting hedging.

4.3.1. Alternative theories and estimators for deriving the optimal hedge ratio

Futures hedging involves creating a simultaneous position in the futures market and spot market of the underlying commodity in order to hedge the fluctuations in commodity prices. Accordingly, the optimal hedge ratio is the proportion of the cash market position that should be covered with an offsetting position in a futures market. Theoretically, the optimal hedge ratio will be different based on the objective function of the optimization process. The earliest and widely implemented approach was to measure the optimal hedge ratio that minimizes the variance of the hedged portfolio (Ederington, 1979; Johnson, 1960; Stein, 1961). The minimum variance (MV) hedge ratio is calculated by regressing cash prices of the hedged commodity on the prices of the relevant futures contract. The slope coefficient of this regression is the MV hedge ratio and R squared of the regression indicates the hedging effectiveness. The MV hedge ratio has become popular because it is easy to understand and to compute.

Nevertheless, MV hedge ratio is not consistent with the mean-variance optimization framework as it does not consider the return of the portfolio. Alternatively, mean–variance optimal hedge ratio was introduced to overcome this drawback (Cecchetti, Cumby and Figlewski, 1988; Hsin, Kuo and Lee, 1994). Thereafter, scholars have introduced several other objective functions to estimate the optimal hedge ratio. Cecchetti et al. (1988) and Lence (1995; 1996) derive the optimal hedge ratio by maximizing an expected utility function. In addition,

[10] Refer to Carlton (1984), Carter (1999), Chen, Lee ad Shrestha (2003), Garcia and Leuthold (2004) and Gray and Rutledge (1971) for literature surveys on commodity futures markets.

Cecchetti et al. (1988) provide evidence that utility maximizing hedge ratio performs better than the MV hedge ratio. Howard and D'Antonio (1984) find the optimal hedge ratio that maximize the Sharpe ratio of a portfolio. Cheung, Kwan and Yip (1990) derived the optimal hedge ratio by minimizing the mean Gini coefficient whereas Kolb and Okunev (1992) derive it based on the mean extended-Gini coefficient. Furthermore, there are several other models: minimum generalized semi-variance (GSV) hedge ratio introduced by De Jong, De Roon and Veld (1997) and optimum mean-GSV hedge ratio introduced by Chen, Lee and Shrestha (2001).

Among all these theoretical models, MV hedge ratio is the widely adopted static hedge ratio (Chen et al., 2003). Figlewski (1984) found that MV hedge ratio is the most effective model compared to other hedging strategies. The MV hedge ratio is estimated by using the Ordinary Least Square (OLS) regression estimator. This model assumes error terms are homoscedastic and ignores the possible existence of heteroscedasticity in error terms and autocorrelation in the residuals of price series. Furthermore, it fails to take into consideration the relevant conditional information available (Myers and Thompson, 1989). Finally, the MV hedge ratio is a static model and hence it is not time-varying. Later studies have introduced different estimators to calculate the MV hedge ratio in order to resolve these limitations in the traditional approach.

In contrast, there is evidence to justify the hedge ratio is time-varying instead of being static. Cecchettie et al. (1988) estimate time-varying hedge ratios using the Autoregressive Conditional Heteroscedasticity (ARCH) model. Later studies started using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to calculate time-varying hedge ratios (Bekkerman, 2011; Choudhry, 2009; Haigh and Holt, 2002; Moschini and Myers, 2002; Myers, 1991). GARCH framework estimates time-varying hedge ratios considering the heteroscedasticity in error terms. Earlier, Myers (1991) concludes that the GARCH hedge ratio performs only marginally better compared with constant hedging performance for wheat in US. However, later studies add evidence to conclude that the time-varying hedge ratios of GARCH model outperform the OLS hedge ratios (Bekkerman, 2011; Choudhry, 2009; Haigh and Holt, 2002; Moschini and Myers, 2002).

Additionally, the Error Correction Model (ECM) is also applied to calculate the MV hedge ratio considering the long-term co-integration of the spot and futures price series of commodities (Ghosh, 1993; Juhl, Kawaller and Koch, 2012; Lien, 1996; Tse, 1995). Kroner and Sultan (1993) and Adams and Gerner (2012) combine the ECM model with GARCH error structure to measure the optimal hedge ratio, taking into account the heteroscedasticity of error terms. In order to consider the existence of autocorrelation in residuals of the spot and futures price series, several studies have used either the Estimated Generalized Least Square (EGLS) model (Brorsen, Buk and Koontz, 1998; Franken and Parcell, 2003) or the Generalized Least Square (GLS) model (Kim, Brorsen and Yoon, 2015). These GLS and EGLS estimators correct for both autocorrelation and heteroscedasticity in time series.

In conclusion, the existing literature suggests that optimal hedge ratio and hedging effectiveness can vary substantially between different theoretical models and statistical estimators adopted. This study will concentrate only on the MV hedge ratios estimated using different statistical estimators mentioned above. Therefore, the sample of the studies selected for this meta-analysis includes studies only estimating the MV hedge ratio using these different estimators.

4.3.2. Factors affecting the optimal hedge ratio and hedge effectiveness

There is no universally appropriate optimal hedge ratio for all types of hedging even though accounting standards have set a single threshold level of hedging effectiveness for all types of hedging. According to existing literature, the following factors affect the level of optimal hedge ratio and the level of hedge effectiveness.

First, hedge horizon affects the optimal hedge ratio and the hedge effectiveness (Chen, Sears and Tzang, 1987; Chen, Lee and Shrestha, 2004; Juhl et al., 2012). The longer the hedge horizon, both hedge ratio and hedge effectiveness increases (Chen et al., 1987; Chen et al., 2004). Furthermore, Juhl et al. (2012) find that hedge effectiveness converges to one when the hedge horizon is extended. On a separate note, Chen et al. (1987) confirm that studies considering hedging using financial futures contracts used shorter hedge horizons compared with hedging using agricultural commodities-based futures contracts.

Second, Laws and Thompson (2005) suggest that the success of futures-based hedging varies across studies depends on whether the hedge is a direct or a cross-hedge, on the type of the commodity and whether in-sample or out-of-sample period is considered. Cross-hedging involves hedging the cash prices of a selected commodity using the futures prices of another (but related) commodity. Anderson and Danthine (1981) provide theoretical framework for cross-hedging. Analyzing the effectiveness of cross-hedge strategies has been carried out in the agricultural commodity sector (Bialkowski and Koeman, 2018; Buhr, 1996; Hayenga and DiPietre, 1982; Newton and Thraen, 2013; Rahman, Turner and Costa, 2001) and in the energy sector (Adams and Gerner, 2012; Franken and Parcell, 2003).

The results of cross-hedging strategies are inconclusive regarding whether cross-hedging or direct hedging is better. According to Franken and Parcell (2003), cross-hedging in the NYMEX unleaded gasoline futures market can reduce the ethanol price risk. However, after the introduction of a futures contract on ethanol, Dahlgran (2009) finds that direct hedging ethanol price risk using ethanol futures contract is more effective than cross-hedging using either unleaded gasoline futures contracts or using Reformulated Gasoline Blend-stock for Oxygen Blending (RBOB) futures contract, except for a one-week hedge horizon. In relation to winter canola, Kim et al. (2015) suggest that cross hedging of winter canola is less effective compared with direct hedging. Furthermore, Bialkowski and Koeman (2018) conclude that

NZX dairy futures are effective for cross-hedging international dairy commodities than CME dairy futures contracts. It is clearly visible, based on these findings, that the level of effectiveness of cross-hedging varies with the type of commodity hedged.

Another alternative to direct hedging is multi-product hedging. It involves hedging using futures contracts of more than one commodity. The multi-product hedging proved to be more beneficial relative to both single product hedging and proportional hedging in locations where the prices of multiple products are highly correlated (Fackler and McNew, 1993). The previous studies conclude: cross-hedging distillers dried gains with soybean meal and corn futures is effective (Miller, 1982a); multi-product hedging feeder pigs with both live hog and corn futures was more effective than using only live hog futures (Miller, 1982b); multi-product hedging mill-feed using both corn and soybean meal futures is better than simple cross-hedging (Miller, 1985) and multi-product hedging using both corn and soybean meal futures contracts successfully reduces the price risk of fishmeal cash prices (Franken and Parcell, 2011).

Third, existing literature has modified the traditional regression model of estimating the optimal hedge ratio by including additional explanatory variables into the model. In order to test the stability of the hedge ratios over time, year dummies were introduced into the traditional OLS regression model (Carter, 1984; Revoredo-Giha and Zuppiroli, 2013). They conclude that adding year dummies could improve hedging effectiveness. Furthermore, controlling for transaction cost has also created a significant effect on optimal hedge ratios (Mattos, Garcia and Nelson, 2008).

Based on the existing literature on derivatives, hedging effectiveness is likely to be determined based on the design of the hedge, hedging horizon, location, type of the contract used, type of the commodity hedged or used for hedging in each study.

4.4. Research Design

4.4.1. Alternative regression models in original studies

As discussed above, there are three types of regression models used to estimate the MV hedge ratio in previous literature.

$$S_t = a_0 + a_1 F_t + e_t \tag{4.1}$$

$$\Delta S_t = a_0 + a_1 \Delta F_t + e_t \tag{4.2}$$

$$R_s = a_0 + a_1 R_f + e_t \tag{4.3}$$

The equation (4.1) regresses the spot prices of the commodity on day t (S_t) on the prices of the futures contract used to hedge on day t (F_t) in levels. In equation (4.2), ΔS_t and ΔF_t denote the price changes of spot prices and the futures prices of commodities and futures contracts. Equation (4.3) regresses commodity spot returns (R_s) on the returns of futures contract (R_f). In all three regression models, a_1 denotes the MV hedge ratio. I have collected these hedge ratio estimates, their respective standard errors and/or t statistics from the sample of studies selected for this meta-analysis. The hedging effectiveness is measured by the R squared of these regressions and gathered into my database.

The debate about the best type of data to use in the regression model of the MV hedge ratio is controversial. The question is whether to use price levels, price changes or percentage changes of prices (returns) in the regression model. There are several arguments set forth by previous researchers. First, price difference regressions or return regressions are more appropriate statistically than price level regressions because residuals of the cash and futures prices are likely to be highly correlated (Benninga, Eldor and Zilcha, 1984; Brown, 1985; Hill and Schneeweis, 1981). These studies argued that either price difference regression or the return-based regression is statically more valid. Despite this debate, price level regression has been extensively used in the literature over time (Altman, Sanders and Schneider, 2008;

Brinker et al., 2009; Chen et al., 2004; Hayenga and DiPietre, 1982; Hayenga, Jiang and Lence, 1996; Heifner, 1972; Miller, 1985; Schroeder and Mintert, 1988).

Second, Ghosh (1993) claims that all the above three types of regression models are mis-specified. According to Ghosh (1993), the model in equation (4.1) is not valid as it does not include the short run dynamics of the relationship between spot prices and futures prices. Although the model is optimized for residual autocorrelation in equation (4.2), it also does not include an error correction term. Finally, the regression model in equation (4.3) is also inaccurate as it ignores the lagged values of these time series. Financial time series are non-stationary but if a linear combination of two time series are stationary, Ghosh (1993) suggests that the error correction model (introduced by Engle and Granger, 1987) is the best estimator to use instead of using the simple OLS regression as mentioned above.

Furthermore, there are different interpretations for the optimal hedge ratio estimated under each of the above three regression model. The hedge ratio derived from equation (4.1) is the ratio of the number of futures contract units to the number of cash position units to be hedged in order to offset the cash position price volatility. The price change regression in equation (4.2) provides the ratio of the proportional number of units of the futures contracts to the proportional number of units of the spot contract. The equation-derived hedge ratio in (4.3) is the ratio of the value of the futures position to the value of the cash position that must be hedged to mitigate the cash position return volatility.

Due to these differences in the interpretation of optimal hedge ratios, it is not possible to combine all the collected hedge ratio estimates into one sample for the meta-analysis. Unfortunately, I do not have the sample sizes (or the degrees of freedom) of the hedge ratio estimates in original studies. Therefore, I could not calculate the Partial Correlation Coefficient (PCC) to remove the problem of this different interpretation and measurement unit in the regression models following general practice in meta-analysis studies. Therefore, this study analyses the data based on three sub-samples depending on the type of regression model: price level, price change and return.

4.4.2. Data sample

The starting point of a meta-analysis is to collect relevant studies on a selected research issue. The objective is to provide research-based evidence regarding what should be the optimal hedge ratio and the level of hedge effectiveness to be considered as the threshold level in the accounting standard. For this purpose, I have searched for papers using these key word combinations: “Hedge ratio and commodity markets”, “Hedging effectiveness and commodity markets”, “Minimum variance hedge ratio and commodity markets”, “Optimal hedge ratio and commodity markets”, “Futures hedging and commodity markets” and “Cross-hedging and commodity markets”. I have collected papers from these electronic databases: Google Scholar, Ebscohost, JSTOR, Science Direct, Research Gate, SSRN and EconRep.

There is no precise number for how many papers ought to be collected or selected for a meta-analysis study. The objective is to conduct a comprehensive search collecting papers relevant for the selected topic and then select the best comparable papers to code. According to Stanley and Doucouliagos (2012), the average number of studies included in 87 meta-analyses they reviewed was 41, with the median being 35. I have selected only 38 papers for coding from a total sample of 406 research papers collected (Appendix 1 provides the list of selected papers). The search for studies was terminated on 5th July 2019. Finally, I have collected 1699 hedge ratio estimates from these 38 papers.

Given the variety of theoretical models adopted to measure the optimal hedge ratio (as discussed in the literature review above), I have restricted this study to collect MV hedge ratios estimated using OLS, GLS, EGLS, ARCH, GARCH, co-integration, ECM and maximum likelihood (ML) estimators. In order to conduct the meta-analysis, I require effect sizes (estimated hedge ratios) and their respective standard errors. Thus, I have omitted studies that do not provide standard errors or any other statistical measures that would allow me to calculate the standard error of the estimated hedge ratio in the original study. Furthermore, I concentrate only on futures contracts-based hedging and exclude the studies on option-based hedging. I have collected papers written in English and excluded papers written in other languages. After considering and eliminating papers based on these criteria, I had 38 papers left for coding.

The selected set of papers represent energy, agriculture, precious metals and livestock commodity markets. These are the sectors included in the Bloomberg Commodity Index. I have gathered all direct hedge ratios, cross-hedge ratios, multi-product hedge ratios and proportional hedge ratios. I have aggregated these hedge ratio estimates for different countries, for different exchanges, on different commodities, for different time periods in one database, assuming the market conditions at the time of each study are similar across countries, exchanges, commodity sectors and across time periods.

4.4.3. Sample characteristics

The papers selected for the study are published within the period from 1972 to 2018. There are 9 studies (25.5% of estimates) published before 1990, 5 studies (39.5% of estimates) published between 1990 and 1999 (inclusive) and 13 studies (35% of estimates) published on or after 2000. The composition of these studies includes papers published in both ranked (31) and non-ranked journals (7) based on the ABDC Journal Ranking system.[11] There are 19 studies published in A and A* ranked journals, 4 in B ranked journals and 7 in C ranked journals. Furthermore, these studies are published in 17 different journals.

Table 4.1 provides the descriptive statistics of the hedge ratios, standard errors, t statistics and R squared values (hedging effectiveness) collected for the three sub-samples. These sub-samples are created based on the type of the regression model used. Accordingly,

[11] Journal ranks are based on the ABDC Journal Ranking System published in 2017. Retrieved from http://www.abdc.edu.au/master-journal-list.php

the mean hedge ratio is 1.33, 0.63 and 0.60 for the level, price change and return sub-samples, respectively. These mean hedge ratios in sub-samples do not fall under the expected threshold level of 0.8 to 1.25 required by the accounting standard. Furthermore, the average hedge effectiveness is 72.9%, 69.4% and 60.1% for the level, price change and return sub-samples, respectively. These statistics suggest that the futures-based hedging in the commodity markets does not meet the threshold level of hedge effectiveness as well. Therefore, it is highly unlikely that futures-based hedging in commodity markets will be eligible for the application of hedge accounting.

[Insert Table 4.1 about here]

In addition, I have summarized the descriptive statistics for the hedge ratios, standard errors, t statistics and R squares based on each commodity sector as well. In summary, I present graphically the average hedge ratio and the hedge effectiveness of each commodity sector in Figure 4.1. These graphs depict that mean hedge ratios and the effectiveness of hedge varies depending on the commodity sector. Surprisingly, none of these commodity sectors have reported a hedge ratio or hedge effectiveness within the expected threshold level required by the accounting standard, except the precious metals sector.

[Insert Figure 4.1 about here]

4.5. Testing for Publication Bias

4.5.1. FAT-PET-PEESE approach

The key research question is what the optimal level of hedge ratio be after correcting for any publication bias existing in the hedging related literature. This study adopts the meta-analysis methodology to measure the true hedge ratio corrected for publication bias. According to Card and Krueger (1995), publication selection bias may arise for three reasons. First, journal editors may tend to publish the papers that have effects consistent with the expected theoretical relationship. Second, it is likely that statistically significant effects will have a greater probability of getting published or being reported. Third, researchers may use the presence of a conventionally expected result as a model selection test. Approving this, Doucouliagos and Stanley (2013) find that most studies in the area of empirical economics suffer from the publication bias. The meta-analysis methodology is now attracting the interest of finance scholars and there is only a handful of meta-analysis studies published in finance to date.[12]

I first test the publication bias using a visual test called Funnel Plot (Egger et al., 1997) and then test statistically using the Funnel Asymmetry Test (FAT) (Card and Krueger, 1995). Figures 4.2 to 4.4 depict the Funnel Plots of the estimated hedge ratios collected from the original studies on the horizontal axis and their respective precision (i.e. the inverse of the standard error of the estimate) on the vertical axis. Figures 4.2 and 4.4 display the possible existence of a positive publication bias relating to the MV hedge ratios calculated based on price level and return data. The wide dispersion in the Funnel Plot indicates the heterogeneity of the MV hedge ratio estimations in the original studies. Figure 4.3 shows that the estimated MV hedge ratios based on price changes is equally distributed with less dispersion.

[Insert Figure 4.2 to Figure 4.4 about here]

The lack of asymmetry in the funnel plot indicates the possible existence of publication bias in the selected research area. In order to validate the statistical significance of what is depicted in the Funnel Plots, this study employs a more statistically validated approach of testing publication bias. The FAT analyses the relationship between the estimated effect size and its standard errors using the following meta-regression model. If there is publication bias,

[12] These are examples of few recent applications of meta-analysis in finance: Arestis, Chortareas, and Magkonis (2015); Asongu (2015); Astakhov, Havranek, and Novak (2017); Bessler, Conlon, and Huan (2019); Bialkowski and Perera (2019); Ewjik, de-Groot, and Santing (2012); Geyer-Klingeberg, Hang and Rathgeber (2019); Rusnak, Havranek and Horvath (2013) and Zigraiova and Havranek (2016) for recent examples of the application of meta-analysis in finance.

the relationship between the estimated hedge ratios and their respective standard errors is expected to be statistically significant.

$$\alpha_{ij} = \beta_0 + \beta_1 SE_{ij} + \varepsilon_i, \tag{4.4}$$

where α_{ij} is the estimated MV hedge ratio from regression *j* in study *i* and SE_{ij} is the standard error of the estimated MV hedge ratio from regression *j* in study *i*. The constant (β_0) measures the overall hedge ratio corrected for the potential publication bias, slope coefficient (β_1) measures the extent of publication bias and ε_i is the error term. Testing the hypothesis $H0$: $\beta 1$ = 0 is known as FAT and testing the hypothesis $H0$: $\beta 0$ = 0 is known as Precision Effect Test (PET). If $H0$: β_1 = 0 is rejected, it implies that there is a publication bias related to the estimated hedge ratios in commodity markets. The direction of the publication bias depends on the sign of the slope coefficient. If $H0$: β_0 = 0 is rejected, it can be concluded that the model has estimated the true hedge ratio after correcting for publication bias.

The OLS estimation of the equation (4.4) above may suffer from heteroscedasticity. Therefore, this study estimates the equation (4.4) using either fixed effects (FE) or random effects (RE) model. The FE model assumes that there is one true effect size which underlies all the studies in the analysis. Following Stanley (2005; 2008), I divide the equation (4.4) by the corresponding standard error. In other words, I use $1/SE_{ij}$ (or known as precision) as the weight 1 of the regression model. The weight 1 ignores the fact that some studies report more estimates compared with others and allocates equal weight to every estimate. This transformation using precision creates the following new regression model.

$$t_{ij} = \beta_1 + \beta_0 \left(\frac{1}{SE_{ij}}\right) + \upsilon_{i,} \tag{4.5}$$

where t_{ij} is the t statistic of the estimated MV hedge ratio from regression *j* in study *i* and $(\frac{1}{SE_{ij}})$ is the inverse of the standard deviation or the precision from regression *j* in study *i*. There are two key assumptions in the FE model. First, fixed effect error variance (υ_i) is assumed to be known and second, the error term will be heteroscedastic.

In equation (4.5), the new constant term β_1 indicates the publication bias and the slope term β_0 indicates the existence of a genuine effect after controlling for publication bias. The hypothesis test would be similar as above. If the results reject $H0$: β_1 = 0, it implies that there is a publication bias and if it rejects $H0$: β_0 = 0, it suggests that the model has estimated the genuine hedge ratio after controlling for publication bias. In weight 2, I multiply $1/SE_{ij}$by the inverse of the number of estimates reported per study ($1/N_i$). This weight 2 assigns equal weight for each study and gives the equal importance for each study but a different weight for each estimate based on the number of estimates reported in each study.

In contrast, RE model assumes a distribution of true effects and assumes these differences in the estimated MV hedge ratios across studies arise due to both sampling error and genuine differences in the underlying hedge ratio estimate itself in original studies. Therefore, the total variability in a hedge ratio estimate consists of two components under the RE model: fixed effect error variance (υ_i) and the estimated variance of the population hedge ratios across studies (τ^2). Accordingly, the weight 1 in the RE model will be as follows.

$$\frac{1}{\sqrt{(SE_{ij})^2+\tau^2}}, \tag{4.6}$$

where SE_{ij} is the standard error of the estimated MV hedge ratio from regression j in study i and τ^2 is the estimated variance of the population hedge ratios across studies. I have estimated τ^2 using *metareg* in Stata (Harbord and Higgins, 2008) under the Restricted Maximum Likelihood method. The weight 2 of the RE model will again be similar to weight 2 under FE model. The weight 1 of the RE model i.e. equation (4.6) will be multiplied again by the $1/N_i$ to give equal importance to each study.

In the PET, when the results reject the $H0$: $\beta_0 = 0$, it concludes that β_0 is the true effect after controlling for publication bias. Stanley and Doucouliago (2012) state that a more accurate correction for publication bias in the meta-regression model can be estimated when the β_0 is significant in PET. They suggest using a non-linear model indicating that the effect is related to the variance i.e. the square of the standard error in the original study instead of using the standard error. This model is known as the precision-effect estimation with standard errors (PEESE) test. The regression model of PEESE will be as follows.

$$\alpha_{ij} = \beta_0 + \beta_1 SE_{ij}^2 + \varepsilon_i, \tag{4.7}$$

where α_{ij} is the estimated MV hedge ratio from regression j in study i, SE_{ij}^2 is the square of the standard error of the estimated MV hedge ratio from regression j in study i and ε_i is the disturbance term. Similar to FAT-PET, I use weight 1 and weight 2 with PEESE as well. For example, the PEESE regression in equation 4.7 after weighting with weight 1 under FE model will be as follows.

$$t_{ij} = \beta_1 SE_{ij} + \beta_0 \left(\frac{1}{SE_{ij}}\right) + \upsilon_i \tag{4.8}$$

This regression model in equation (4.8) does not include a constant term now. In PEESE also, the hypothesis test is $H0$: $\beta_0 = 0$. If β_0 is significant, the study further convince that the model provides genuine hedge ratio estimate after controlling for publication bias.

This FAT-PET-PEESE procedure is a valid method of analysis and has adopted in several recent studies in economics and finance literature: Churchill and Yew (2017), Costa-Font, Gemmill, and Rubert (2011), Efendic, Pugh, and Adnett (2011), Havránek (2010), Iwasaki and Tokunaga (2014), Kim, Doucouliagos and Stanley (2014) and Linde Leonard, Stanley, and Doucouliagos (2014). Therefore, this study also follows the same methodology adopted by the previous meta-analysis researchers.

4.5.2. FAT-PET-PEESE results

This section summarizes the results of the FAT-PET-PEESE tests and analyses the results thereof. Table 4.2 summarizes the FAT and PET results for each sub-sample: price level, price change and return. Second and third columns provide results for the FE model with weight 1 and weight 2, respectively. Fourth and the fifth columns provide results for the RE model with weight 1 and weight 2, respectively.

[Insert Table 4.2 about here]

In the sub-sample of price level, this study finds positive publication bias under FE and RE models with weight 1 but negative publication bias under FE model with weight 2 only. The evidence of the existence of publication bias related to hedge ratio estimates in commodity markets is not consistent. The PET results reject the $H0$: $\beta_0 = 0$ under all models except RE model with weight 2. Thus, I conclude that these models have estimated the true hedge ratios after correcting for publication bias. The average hedge ratio estimate of the price level sub-sample lies between 0.6953 and 1.0333.

In the price change sub-sample, there is no strong evidence of the existence of significant publication bias except under the FE model. However, the results of the FE models are also not consistent. With weight 1, there is a negative publication bias whereas with weight 2, there is a positive publication bias. However, there are robust results to conclude that the overall hedge ratio estimate in this sample is positive and lies between 0.6049 and 1.1663 after correcting for publication bias.

In relation to the return sub-sample, the FE regression model provides evidence for the existence of negative publication bias related to the hedge ratio of commodity markets. The RE models do not provide evidence of publication bias. Furthermore, the results suggest that the overall hedge ratio is positive and lies between 0.6395 and 0.9040 after controlling for publication bias.

In summary, there is no solid proof of the existence of publication bias related to hedge ratio estimates in commodity markets. Nevertheless, the results confirm that the overall estimate of the hedge ratio after controlling for publication bias is positive and on average, lies between 0.60 and 1.20. Hence, these findings question the appropriateness of the threshold hedge ratio set by the accounting standard (i.e. 0.80 to 1.25 or 80% to 125%).

As a robustness check and to improve the accuracy of this true hedge ratio estimate, the analysis is extended and the PEESE test is conducted. Table 4.3 presents the results of the PEESE test. This test is conducted using the FE model with weight 1 and weight 2 and RE model with weight 1 only. I excluded the RE model with weight 2 in the PEESE as β_0 coefficients of PET analysis in the above were not significant for this model. The results show that the true hedge ratio estimates are positive and significant. On average, the true hedge ratio lies between 0.62 – 1.24, 0.60 – 1.15 and 0.60 – 0.85 for price level, price change and return sub-samples, respectively. Based on these findings, I argue that the minimum level of the threshold hedge ratio in the accounting standard should be lowered to 0.60 instead of 0.80.

[Insert Table 4.3 about here]

Furthermore, this study has conducted the FAT-PET-PEESE test for each commodity sector under each sub-sample of price level, price change and return as well. I do not present these results in this chapter (but are available on request). Even in that analysis, I could not find any strong and consistent evidence regarding the existence of publication bias in relation to the hedge ratio estimates in each commodity sector. Nevertheless, I found the model is estimating the true hedge ratio, but it varies significantly between commodity sectors. Based on that, I question the appropriateness of setting a common threshold hedge ratio for all different types of commodity sectors.

4.6. Heterogeneity of Estimated Hedge Ratios

The factors explaining the heterogeneity in meta-regression can be classified into two broad categories: structural heterogeneity and methodological heterogeneity. The structural heterogeneity includes real differences among the primary studies whereas methodological heterogeneity includes factors that explain difference in the study design and the methodology used. I have identified the characteristics of data, geographical location, commodity sector and publication characteristics to explain the structural heterogeneity in the original studies. The design of the hedge, estimation method and other control variables included in the model could explain the methodological heterogeneity in original studies.

Accordingly, there are 43 different variables identified from original studies that could possibly explain the variation in the estimated hedge ratios in commodity markets. Table 4.4 lists these explanatory variables and provides their definitions. The existing literature confirms that the estimation method, hedging strategy, hedge horizon and the inclusion of control variables affect the optimal hedge ratio. This study includes publication characteristics that might possibly have an impact on the estimated hedge ratio, following the previous meta-analysis studies in economics and finance (Arestis et al., 2015; Astakhov et al., 2017; Bessler et al., 2019; Chruchill and Yew, 2017; Geyer-Klingeberg et al., 2019; Zigraiova and Havranek, 2016).

[Insert Table 4.4 about here]

All these variables are manually coded by reading the selected sample of 38 papers. There is a selection bias involved because the variables are selected based on the availability of data in the original studies. Table 4.5 summarizes the unweighted and weighted (by 1/SE) descriptive statistics (mean and standard deviation) of these variables and results are explained in detail under each of the following sub-sections.

[Insert Table 4.5 about here]

4.6.1. Data characteristics

Data characteristics include the standard error (SE) of the estimated hedge ratio and the MidYear of the sample period in the original study. Theoretically, the meta-regression model suggests that the estimated hedge ratios in original studies relate with their respective standard errors. The average SE is 0.14, 2.43 and 0.11 for sub-samples of price level, price change and returns, respectively.

This study includes the MidYear of the sample period in original studies to control for any structural changes in the original data. The average MidYear is 1987, 1992 and 2004 for the price level, price change and return sub-samples, respectively. This indicates that researchers have first used the price level-based regression model and then moved into the price change regression model due to the statistical issues with price levels. In recent years, return-based regression model has become widely popular among researchers.

4.6.2. Hedge horizon

To account for differences in the hedge horizon, this study uses the frequency of the data used in original studies. I have created three dummy variables: Daily, Weekly and Reference Frequency (includes all the other data frequencies). In all sub-samples, more than 50% of the original studies used daily frequency data. Price level and return sub-samples use weekly data as the second-best popular data frequency. Price change sub-sample has both weekly (17%) and reference frequency data (17%) equally.

4.6.3. Design of the hedge

The design of the hedging strategy in the study also influences the hedge ratio estimate of the study. As discussed in the literature review, the type of hedging affects the hedge ratio estimates. I have created three dummy variables to represent the type of hedging involved. The Own-hedge variable equals one if the underlying commodity of the futures contract is the same as the commodity hedged in the study. The Cross-hedge variable equals one when the original study uses a futures contract of a closely related commodity to hedge the exposure of the commodity concerned. Cross-hedge involves the use of a single related commodity to hedge the commodity concerned. The Multi-hedge variable equals one when the original study uses more than one cross-hedge contracts to hedge the exposure of the commodity in question. The 96% of studies in the price level sub-sample used cross-hedging strategy, 66% of the price change sub-sample used own hedge strategy and 40% of the return sub-sample used multi-hedge strategies in most.

4.6.4. Geographical location

To address the diversity of commodity exchanges involved in original studies, I have created eight dummy variables representing exchanges. The exchanges include Chicago Board of Trade (CBOT), Chicago Mercantile Exchange (CME), Intercontinental Exchange (ICE), London International Financial Futures and Options Exchange (LIFFE), Marché à Terme International de France (MATIF), Minneapolis Grain Exchange (MGEX), New York Mercantile Exchange (NYMEX) and New Zealand's Exchange (NZX). The omitted category represents any other than these exchanges. A majority of studies (93%) in the price level sub-sample use futures contracts traded in CME and other two sub-samples use futures contracts traded in CBOT (41% and 69% in price change and return sub-samples, respectively).

4.6.5. Commodity sector

The differences in the commodity sector is another crucial variable in the original studies. I have collected MV hedge ratio estimates for different commodity sectors: agriculture, energy, livestock and precious metals.[13] I created four dummy variables for agriculture, energy, livestock and precious metals sector (either one of these will be the reference category depending on the availability of data). In the price level sub-sample, 92% of the hedge ratios

[13] This classification of commodity markets is based on the classification used in the Bloomberg Commodity Index.

are estimated for livestock sector. In the price change and return sub-samples, 72% and 82% of the hedge ratios are estimated for agriculture sector.

4.6.6. Estimation methods

The original studies have used different estimation procedures to calculate the MV hedge ratio as discussed in the literature review. These different estimators are captured by creating six dummy variables for Ordinary Least Square (OLS), Generalized Least Square (GLS), Co-integration, Error Correction Model (ECM), Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model and Maximum Likelihood (ML) model and Other category includes any other estimators. The widely adopted estimator is OLS in all three sub-samples.

4.6.7. Differences in control variables

When estimating the MV hedge ratio, some original studies have included other control variables in the regression model depending on the estimation method. I categorized these control variables broadly into four categories such as lags (including lags of future prices and/or spot prices), other commodities, time dummies and basis variables. Any other control variables included are represented by the omitted category. Adding basis variable is the most common (41%) in the price level sub-sample; adding lags is the most common (38%) in the price change sub-sample and adding other commodities is the most common (40%) in the return sub-sample.

4.6.8. Publication characteristics

To account for differences in the publication quality, I include the publication year (PubYear), impact factor of the journals[14] and dummy variables to show the journal rankings. The Rank A, Rank B and Rank C dummy variables take the value of one when the ABDC rank of the journal is A, B or C, respectively. The No Rank category includes journals that do not have

[14] Impact factor of the journal is obtained from https://ideas.repec.org.

any ABDC ranking. Furthermore, I have added the Scimago journal rankings as well. The Scimago<1, Scimago<2 and Scimago>2 dummy variables are equal one when the Scimago ranking is less than one, Scimago ranking is less than two but greater than one and Scimago ranking is greater than 2. The No Rank category includes the journals that do not have a Scimago ranking.

4.7. Results of Meta-Regression Analysis

4.7.1. Methodology

When there are large number of explanatory variables in a regression model, there is model uncertainty regarding the best predictors of the dependent variable and hence, uncertainty regarding what variables should be included in the final model. The Bayesian Model Averaging (BMA) (Zeugner, 2011) handles this model uncertainty problem. BMA is used to resolve the model uncertainty problem in previous meta-regression studies as well (Chruchill and Yew, 2017, Zigraiova and Havranek, 2016).

BMA will run 2^{43} possible combinations of regressions with explanatory variables in this study. BMA calculates three important statistics: posterior mean, posterior standard deviation and posterior inclusion probability. The posterior mean is the average of the coefficients over all models. Posterior standard deviation describes the uncertainty in the coefficient. The posterior inclusion probability (PIP) indicates the probability of a specific variable being included in the true model. Following Zigraiova and Havranek (2016), the effect is considered to be a weak effect when the PIP lies within the range of 0.5 to 0.75, substantial when the PIP is between 0.75 and 0.95, strong when the PIP is between 0.95 and 0.99, and extremely strong when the PIP exceeds 0.99.

This study has conducted the BMA with weighted variables (weighted by 1/SE) for three sub-samples separately. Therefore, it runs the following meta-regression models including the variables selected based on PIP values of BMA results. I have selected variables with a PIP value greater than 0.5 to be included in the meta-regression model.

$$t_{ij} = \beta_1 + \beta_0 \frac{1}{SE_{ij}} + \sum_{k=1}^{K} \delta_k \frac{Z_{ik}}{SE_{ij}} + \eta_j + \varepsilon_{ij}, \tag{4.9}$$

where t_{ij} is the *t* statistic of the estimated MV hedge ratio from regression *j* in study *i* and $(\frac{1}{SE_{ij}})$ is the inverse of the standard deviation or the precision from regression *j* in study *i*. Z_{ik} is a vector of explanatory variables that are likely to explain the heterogeneity in estimated hedge ratios and *k* represents the number of moderating variables. These explanatory variables are also weighted by the $(\frac{1}{SE_{ij}})$ of the regression *j* in study *i*. The hypotheses tested are $H0$: $\beta_0 = 0$ and $H0$: $\delta_k = 0$ i.e. whether each individual coefficient of other explanatory variables equal to zero. If any δ_k coefficients are significant, I conclude that variable as an important factor that determines the heterogeneity in estimated hedge ratios in commodity markets.

4.7.2. Results of the price level sub-sample

This section summarizes the results of the above BMA model and analyses these results. Table 4.6 summarizes the meta-regression results of the price level sub-sample. After removing reference categories and variables which are multicollinear, only 17 variables (including the precision) were included in the BMA exercise of the price level sub-sample. All these variables (except Rank A dummy variable) have a decisive impact on the estimated hedge ratio as their PIP value exceeds 0.99. Therefore, the OLS regression included 16 variables identified as important in the BMA. Furthermore, the standard errors were clustered at the individual study level in the OLS regression.

[Insert Table 4.6 about here]

These results indicate the existence of negative publication bias after controlling for all other moderator variables. It means that negative and significant hedge ratio estimates are more likely to be reported and published compared with positive hedge ratio estimates. The results suggest that the following variables explain the heterogeneity in hedge ratios. When the MidYear increases (i.e. for recent studies), the hedge ratio is likely to increase by 0.55. Hedge ratio estimates are likely to be greater for daily and weekly hedge horizons compared with monthly frequency. The hedge ratio is higher for cross-hedging by 17.8 compared with own-hedging. The models including time dummies are likely to report a higher estimated hedge ratio in original studies compared with models including any other control variables. The higher the impact factor of the journal, the higher will be the value of the hedge ratio reported.

In contrast, the hedge ratio estimates for the livestock sector is lower by 5.8 compared with hedge ratio estimates for agriculture sector. The hedge ratio estimated using OLS estimator is likely to be lower compared with that estimated using the GLS estimator. In the original studies, models including more than one commodity, lags of futures prices or spot prices and basis variable also estimate a lower hedge ratio compared with models including any other control variables. The recently published studies suggest that the higher the PubYear, the lower will be the hedge ratio. Finally, studies published in ranked journals with either Rank B in ABDC ranking or with less than 2 in Scimago, are likely to report a lower hedge ratio.

In summary, these results support the notion that characteristics of data, commodity sector, design of the hedge, estimation methodology, other control variables included in the original study and publication characteristics affect the heterogeneity in hedge ratios in the price level sub-sample. The location of the exchange does not have an impact on the hedge ratio in this sub-sample.

4.7.3. Results of the price change sub-sample

Table 4.7 reports the BMA results of the price change sub-sample. This test included only 30 variables (including the precision) to represent different characteristics. Out of that, only 17 variables were selected based on the PIP value to be included in the OLS regression model.

[Insert Table 4.7 about here]

There is evidence of the existence of negative publication bias in the price change sub-sample after controlling for all these explanatory variables. It means that positive and insignificant hedge ratio estimates are unlikely to get published or reported. However, PIP values are not sufficient to include the variables indicating the characteristics of data and the design of hedging in this sub-sample. This implies that characteristics of data and the design of hedging do not affect the estimated hedge ratios in the price change sub-sample.

As for the location, hedge ratio estimates for different exchanges tend to be lower compared with the reference category of other exchanges. For CBOT, ICE, CME and NYMEX hedge ratio estimates will be lower by 0.28, 1.49, 1.20 and 2.00, respectively compared with the omitted exchange. With reference to the estimation method, estimating the equation (4.2) using cointegration technique reduces the hedge ratio estimate by 0.42 whereas estimating it using GARCH increases the hedge ratio by 0.23. By including lags of futures prices and/ or spot prices of commodity hedged, this reduces the hedge ratio estimate by 0.48. The multi-product hedging reduces the hedge ratio by 0.53. All publication characteristics have relatively high PIP values. However, the findings related to the publication quality are different from each other. When ABDC ranking is used to indicate the publication quality, studies with a ABDC ranking tend to report higher hedge ratios. When the Scimago ranking is used, to indicate publication quality, studies tend to report lower hedge ratios.

In summary, the exchange involved, commodity sector, estimation method, other controlling variables and publication characteristics do indeed matter regarding heterogeneity in hedge ratio estimates in the price change sub-sample.

4.7.4. Results of the return sub-sample

Table 4.8 presents the BMA results of the return sub-sample. After removing reference categories, only 25 variables (including the precision) were included in the BMA exercise. Except for the cross-hedge dummy and time dummy, all other variables reported a PIP value greater than 0.5 and hence were selected as important enough to be included in the OLS regression model.

[Insert Table 4.8 about here]

The OLS regression of these variables excludes the precision and CME dummy variables due to multicollinearity. Hence, these results do not provide evidence of a relationship between the hedge ratio estimate and its standard error for this sub sample. Out of 23 variables added into the OLS regression, only six variables were statistically significant: Daily dummy, ICE dummy, Maximum Likelihood (ML) dummy, Other Commodities dummy, Rank A and Rank C dummies. Accordingly, hedge ratio estimates in the return sub sample are likely to be high when using the daily hedge horizon, ML estimator and for Rank A and C based on ABDC ranking. These hedge ratio estimates are likely to be low for studies involving ICE exchange and those including the prices of multi-commodities in the original model.

In summary, only a few variables representing the exchange involved, hedge horizon, estimation method, other control variables and publication characteristics affect the hedge ratio estimates in the return sub-sample.

4.8. Conclusion

This study aims to fill the gap in the derivative literature by adding empirical evidence to justify the appropriateness of the threshold hedge ratio level and the hedge effectiveness level set by the derivative accounting standards. In order to achieve this objective, I have conducted a meta-analysis study using a sample of 1699 hedge ratio estimates (collected from 38 papers) showing the relationship between spot prices and futures prices in commodity markets.

The results indicate the true hedge ratio in the commodity market lies approximately between 0.60 and 1.20. I suggest policy makers lower the hedge ratio threshold to 0.6 to 1.2 as it is the average level of hedge ratio found, based on the previous literature on commodity futures hedging. Lowering this threshold level will provide the opportunity for more firms trading derivatives to be able to qualify for hedge accounting. This would allow these companies to delay recognizing the changes in the fair value of derivatives and hedged items in the income statement of the firm and hence would help to ensure the survival of these firms during financially vulnerable times.

The average hedge effectiveness (R squared) level in these three sub-samples was in the range of 60% to 73%. Therefore, the suitability of the threshold hedge ratio level of 80% to 125% and the hedge effectiveness level of 80% or above set forth by the accounting standard is questionable. The results also showed that the estimate of the average hedge ratio varies among various commodity sectors.

Furthermore, there is no strong, consistent evidence of the existence of publication bias related to the hedge ratio estimates in the commodity markets based on the FAT results. However, meta-regression results of the price level and price change sub samples provide evidence of negative publication bias after controlling for all other explanatory variables included in the model. Finally, this study provides supportive evidence regarding the notion that characteristics of data, commodity sector, estimation methodology, other control variables included, and the publication characteristics are the key determinants of heterogeneity in the estimated hedge ratios of commodity markets.

Based on these findings, I propose policy makers consider revising this common hedging effectiveness threshold specified in the accounting standard. Based on the findings of this study, I propose two changes. First, the cut-off hedge ratio level should be set in the range of 0.60 to 1.20 (or between 60% and 120%) and the hedge effectiveness should also be lowered to be 60%. Second, I propose the accounting standard setters vary this threshold level depending on the type of the hedge and type of the asset. Finally, it would be more beneficial if the accounting standard can specify best practice to estimate hedge effectiveness and provide alternative practices as well. Proper guidance would reduce the vague understanding of how to estimate hedge effectiveness and also enhance comparability.

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Appendix 1

List of papers selected for the study

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Appendix 2

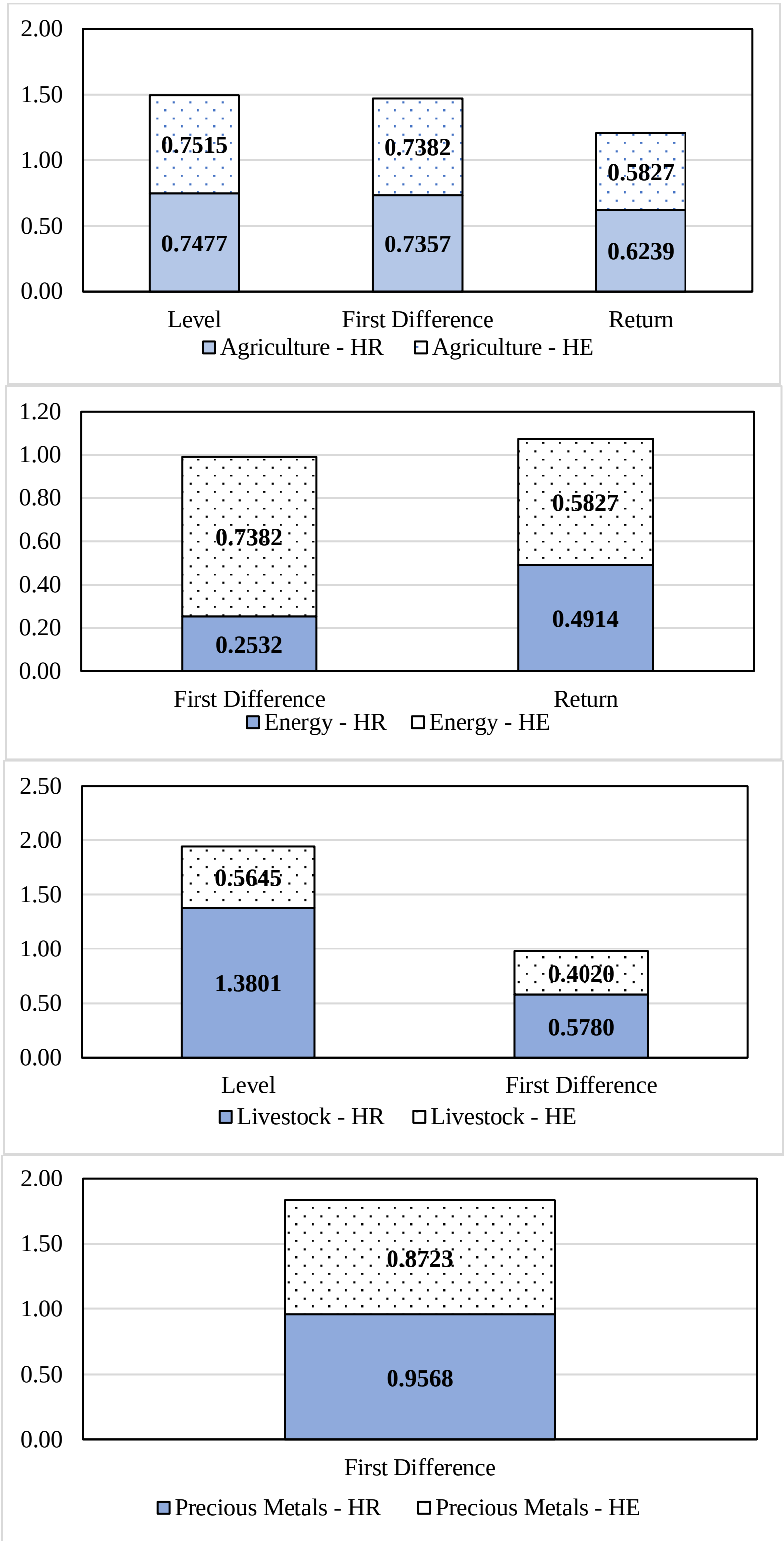

Figure 4.1: Mean hedge ratio and hedge effectiveness by commodity sector
Source: Authors' work

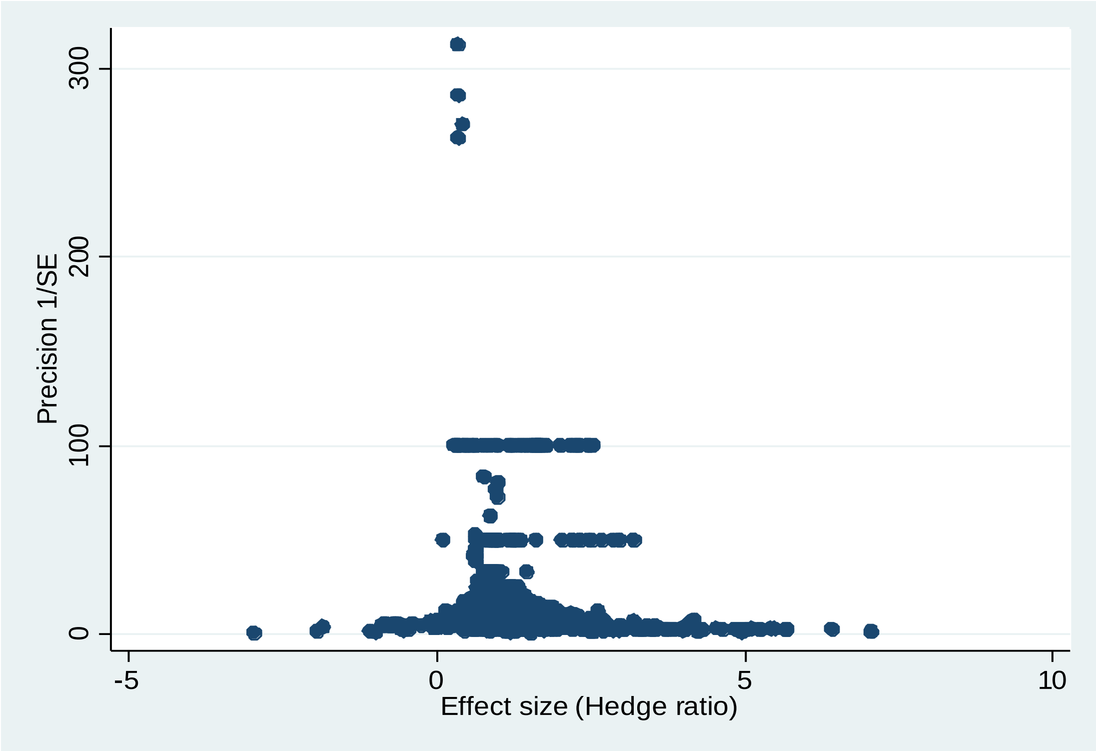

Figure 4.2: Funnel plot of hedge ratios – Price level
Source: Authors' work

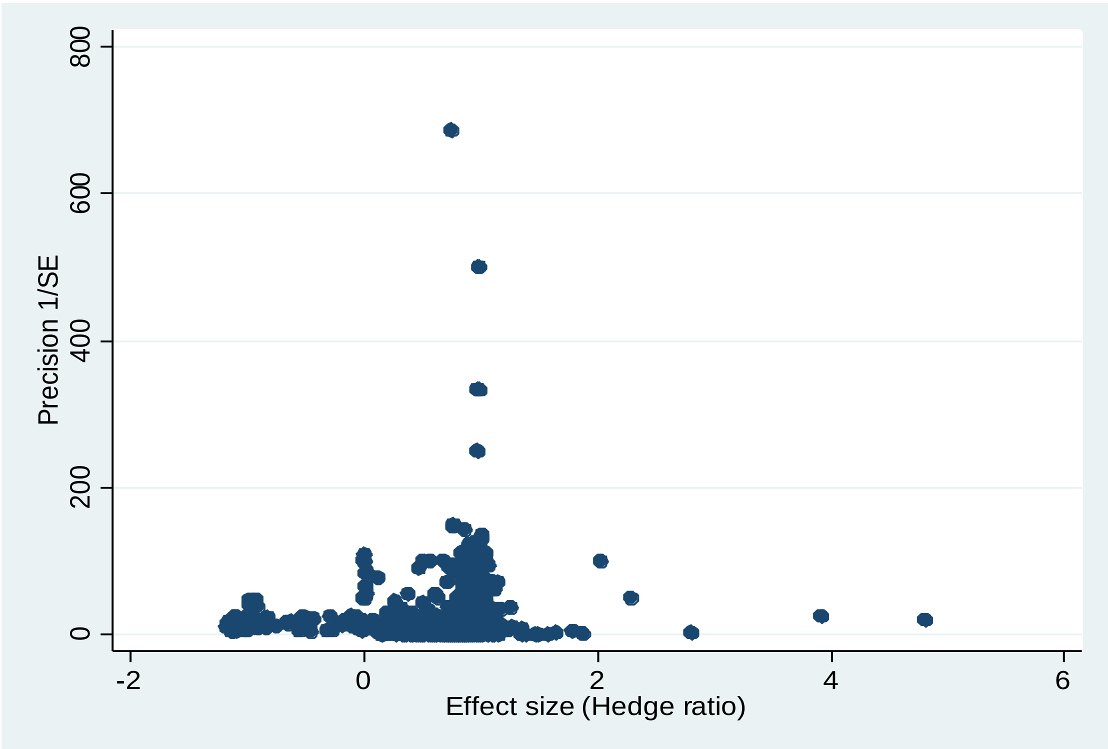

Figure 4.3: Funnel plot of hedge ratios – Price change
Source: Authors' work

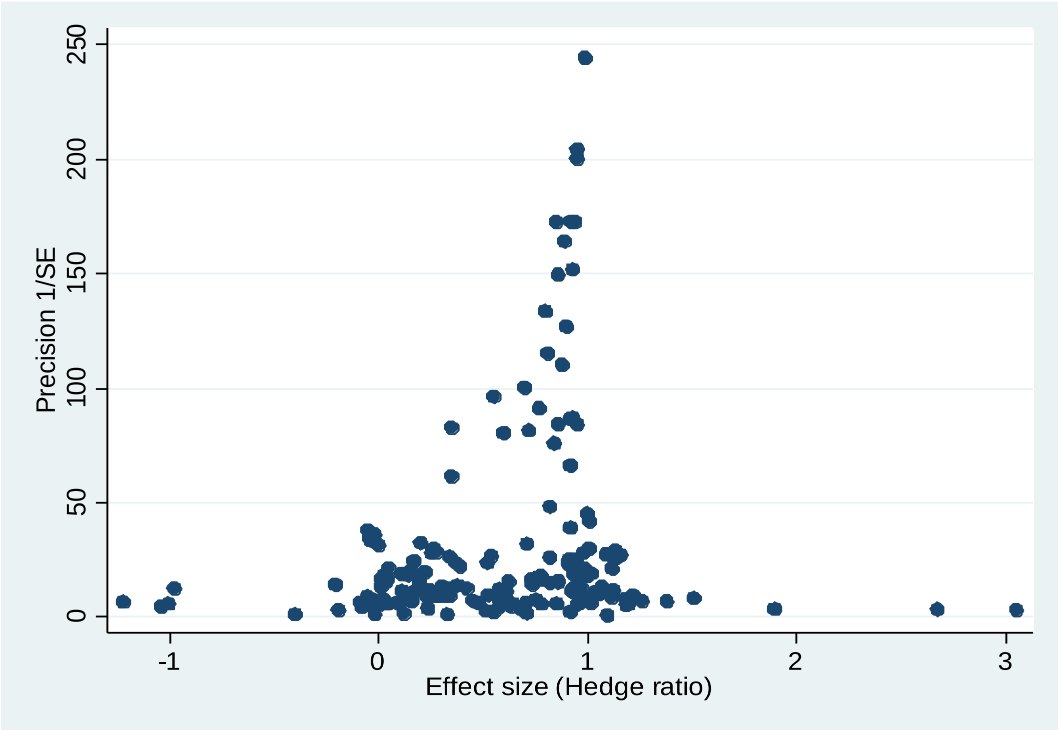

Figure 4.4: Funnel plot of hedge ratios – Returns
Source: Authors' work

Appendix 3

Table 4.1: Descriptive statistics

This table summarizes the mean, minimum and maximum values, standard deviations, skewness and the kurtosis of the minimum variance (MV) hedge ratios, standard errors, t statistics and R squared values in the original studies. The results are reported for three sub-samples based on the type of the regression: price level, price change and returns. The data are collected from 38 selected papers given in the Appendix 1.

Type of the Regression	Variable	Observations	Mean	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis
Price level	Effect size (Hedge ratio)	863	1.3332	-2.9500	7.0600	0.9753	1.4207	8.8162
	Standard error	863	0.1409	0.0032	1.7791	0.1534	3.4751	25.1519
	T statistic	863	25.0600	-7.3600	255.0000	38.8193	3.4561	15.7748
	R squared	546	0.7294	0.0700	0.9700	0.2004	-1.1512	3.7053
Price change	Effect size (Hedge ratio)	625	0.6326	-1.1710	4.8100	0.6402	-0.5507	7.9024
	Standard error	625	2.4258	0.0015	42.7200	6.5029	3.1208	12.8158
	T statistic	625	59.1767	-27.3750	728.0000	156.0817	3.6801	15.4043
	R squared	558	0.6941	0.0000	1.0000	0.2468	-1.0025	3.3222
Returns	Effect size (Hedge ratio)	211	0.6013	-1.2220	3.0540	0.5275	0.1097	6.1638
	Standard error	211	0.1146	0.0041	1.5208	0.1751	4.7585	30.7186
	T statistic	211	18.2678	-12.2375	241.4800	38.2271	3.2410	14.1602
	R squared	154	0.5405	0.0003	0.9400	0.2682	-0.5288	2.3073

Source: Author’s work

Table 4.2: Funnel Asymmetry Test (FAT) and Precision Effect Test (PET) results

This table reports coefficients of β_1 (FAT) and β_0 (PET), respectively for the three sub-samples: price level, price change and returns. The top value is the coefficient estimate and the value in parentheses is the associated standard error. The first two columns provide the results under Fixed Effect (FE) model with weight 1 and 2, respectively. The third and fourth columns provide the results under Random Effect (RE) model with weight 1 and 2, respectively. With weight 1, each estimate is given an equal weight and with weight 2 each study is given an equal weight. FE and RE estimates have robust standard errors clustered by the StudyID. Price level, price change and return sub-samples have 863, 625 and 211 observations, respectively. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	FE with Weight 1	FE with Weight 2	RE with Weight 1	RE with Weight 2
Price level				
FAT (β_1)	**4.5324*** **	**-4.7037*** **	**2.1706*** **	-2.5948
	0.0414	1.2709	0.2255	15.1872
PET (β_0)	**0.9760*** **	**0.6953*** **	**1.0333*** **	0.6578
	0.0011	0.0245	0.0403	0.6552
Observations	863	863	863	863
Price change				
FAT (β_1)	**-5.1769*** **	**2.1777** **	-0.0117	-1.0747
	0.0464	0.8681	0.1006	6.1567
PET (β_0)	**0.9066*** **	**1.1197*** **	**0.6049*** **	**1.1663** **
	0.0007	0.0179	0.0303	0.5797
Observations	625	625	625	625
Returns				
FAT (β_1)	**-5.0911*** **	**-5.2340*** **	-0.3823	0.2028
	0.0843	1.5711	0.3484	12.4709
PET (β_0)	**0.9040*** **	**0.7735*** **	**0.6395*** **	0.5088
	0.0017	0.0579	0.0459	0.9091
Observations	211	211	211	211

Source: Author's work

Table 4.3: PEESE test results

This table reports coefficients of the PEESE test for the three sub-samples: price level, price change and return. The top value is the coefficient estimate and the value in parentheses is the associated standard error. The second and third columns provide the results under Fixed Effect (FE) model with weight 1 and 2, respectively. The fifth column provide the results under Random Effect (RE) model with weight 1. With weight 1, each estimate is given an equal weight and with weight 2 each study is given an equal weight. FE and RE estimates have robust standard errors clustered by StudyID. Price level, price change and return sub-samples have 863, 625 and 211 observations, respectively. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	FE with Weight 1	FE with Weight 2	RE with Weight 1
Price level			
β_0 (True Effect)	**1.0411**** 0.0009	**0.6208***** 0.0121	**1.2456***** 0.0308
SE	**6.7346***** 0.1649	-16.8576 12.6184	
SE/SQRT(Total Variance)			**2.0192***** 0.3232
Price change			
β_0 (True Effect)	**0.8654***** 0.0006	**1.1475***** 0.0141	**0.6041***** 0.0295
SE	-0.0048 0.0058	-0.0305 0.5465	
SE/SQRT(Total Variance)			0.0006 0.0058
Returns			
β_0 (True Effect)	**0.8468***** 0.0014	**0.6480***** 0.0399	**0.6088***** 0.0351
SE	**-5.6241***** 0.3311	-20.0422 13.6690	
SE/SQRT(Total Variance)			-0.1726 0.4249

Source: Author's work

Table 4.4: Determinants of the heterogeneity in hedge ratios

This table defines the variables included in the meta-regression analysis as possible explanatory variables of the heterogeneity in the estimated hedge ratios in original studies. These variables are coded from the list of studies included in the Annexure 1.

Variable	Description
Data Characteristics	
T statistic	The estimated hedge ratio divided by the respective standard error of the estimate
Precision	Inverse of the standard error of the estimated hedge ratio
MidYear	The mean year of the sample period
Hedge Horizon	
Daily	Equals 1 if the daily data is used in the original study
Weekly	Equals 1 if the weekly data is used in the original study
Reference: Other	Equals 1 if any other frequency of data is used in the original study
Design of the Hedging	
Own-hedge	Equals 1 if commodity hedged and the underlying commodity of the futures contract are same
Cross-hedge	Equals 1 if commodity hedged and the underlying commodity of the futures contract are close substitutes or highly correlated
Multi-hedge	Equals 1 if multiple futures contract on different commodities used to hedge at the same time
Reference: Other	Equals 1 if any other hedging strategy is involved
Exchange Involved	
CBOT	Equals 1 if the futures contracts used in hedging are traded in Chicago Board of Trade
CME	Equals 1 if the futures contracts used in hedging are traded in Chicago Mercantile Exchange
ICE	Equals 1 if the futures contracts used in hedging are traded in Intercontinental Exchange or Winnipeg Commodity Exchange
LIFFE	Equals 1 if the futures contracts used in hedging are traded in London International Financial Futures and Options Exchange

MATIF	Equals 1 if the futures contracts used in hedging are traded in Marché à Terme International de France
MGEX	Equals 1 if the futures contracts used in hedging are traded in Minneapolis Grain Exchange
NYMEX	Equals 1 if the futures contracts used in hedging are traded in New York Mercantile Exchange
NZX	Equals 1 if the futures contracts used in hedging are traded in New Zealand Exchange
Reference: Other	Equals 1 if the futures contracts used in hedging are traded in Kansas City Board of Trade or Korea Exchange or any other exchange
Commodity Sector	
Agri	Equals 1 if hedging involves an agricultural commodity (excluding livestock)
Energy	Equals 1 if hedging involves a commodity from the energy sector
Livestock	Equals if hedging involves a livestock
Reference: Other	Equals 1 if hedging involves a precious metal
Estimation Method	
OLS	Equals 1 if ordinary least squares is used to estimate the hedge ratio
GLS	Equals 1 if generalized least squares method is used to estimate the hedge ratio
Co-integration	Equals 1 if co-integration estimator is used to estimate the hedge ratio
ECM	Equals 1 if error correction model is used to estimate the hedge ratio
Reference: Other	Equals 1 if any other estimation method is used to estimate the hedge ratio
Control Variables	
Lag	Equals 1 if lags of cash prices and/or futures prices are included in the estimation equation
Commodities	Equals 1 if multiple commodities are included in the estimation equation
Time	Equals 1 if time dummies (monthly dummies, year dummies, seasonal dummies) are included in the estimation equation
Basis	Equals 1 if basis lags or basis at the beginning are included in the estimation equation
Reference: Other	Equals 1 if any other control variables are included in the estimation equation

Publication Characteristics

PubYear	The year in which the paper is published
Impact factor	The impact factor of the journal in which the paper is published obtained from https://ideas.repec.org
ABDC Rank A	Equals 1 if the ABDC ranking of the journal is A or A*
ABDC Rank B	Equals 1 if the ABDC ranking of the journal is B
ABDC Rank C	Equals 1 if the ABDC ranking of the journal is C
Reference: No Rank (ADBC)	Equals 1 if there is no ABDC ranking for the journal
Scimago (Q<1)	Equals 1 if the Scimago ranking of the journal is less than 1
Scimago (Q<2)	Equals 1 if the Scimago ranking of the journal is less than 2 but greater than 1
Scimago (Q>2)	Equals 1 if the Scimago ranking of the journal is greater than 2
Reference: No Rank (Scimago)	Equals 1 if there is no Scimago ranking for the journal

Source: Author's work

Table 4.5: Descriptive statistics of meta-regression variables

This table summarizes the mean and the standard deviation (SD) of the explanatory variables included in the meta-regression analysis to explain the heterogeneity in the estimated hedge ratios in original studies. These variables are coded from the list of studies included in the Annexure 1. The weighted descriptive statistics are calculated by dividing the value of each variable by the respective standard error of the hedge ratio estimate.

	Price level		Price change		Return		Price level		Price change		Return	
Variable	Mean	SD	Mean	SD	Mean	SD	Weighted Mean	Weighted SD	Weighted Mean	Weighted SD	Weighted Mean	Weighted SD
Data Characteristics												
Standard Error/ FE Precision	0.1409	0.1534	2.4258	6.5029	0.1146	0.1751	20.9900	30.2952	32.3254	54.9687	28.4920	40.3843
MidYear	1987.5900	5.9566	1992.3500	13.4118	2004.1040	9.1557	41750.0740	60439.3299	64304.7000	109268.4000	57059.7600	80830.7400
Hedge Horizon												
Daily	0.5562	0.4971	0.6560	0.4754	0.6493	0.4783	8.7070	20.7459	26.6339	56.7269	24.6072	42.1870
Weekly	0.4299	0.4953	0.1696	0.3756	0.2844	0.4522	11.8498	26.2822	3.0794	8.4858	3.1139	6.2531
Reference: Other	0.0116	0.1071	0.1744	0.3798	0.0664	0.2495	0.2558	2.7528	2.6121	7.1682	0.7709	2.9952
Design of the Hedging												
Own-hedge	0.0382	0.1919	0.6608	0.4738	0.3270	0.4702	0.7415	6.1485	25.0149	54.5356	18.9134	43.4573
Cross-hedge	0.9606	0.1947	0.1728	0.3784	0.2654	0.4426	20.1906	30.1580	4.7956	19.6292	4.0064	7.9906
Multi-hedge	0.0012	0.0340	0.1648	0.3713	0.4076	0.4926	0.0579	1.7020	2.5012	7.2496	5.5722	9.3495
Reference: Other			0.0016	0.0400					0.0136	0.3390		
Exchange Involved												
CBOT	0.0637	0.2444	0.4112	0.4924	0.6919	0.4628	4.4007	24.2216	12.9684	43.0479	13.6949	25.6913
CME	0.9363	0.2444	0.1888	0.3917	0.0284	0.1666	16.5893	21.8471	3.5267	29.7898	0.4234	2.5738
ICE			0.0128	0.1125	0.0948	0.2936			0.1424	1.5729	1.9549	6.4811
LIFFE					0.0474	0.2130			0	0	4.6931	24.1742
MATIF					0.0948	0.2936			0	0	7.2183	29.6658
MGEX			0.0224	0.1481	0.0379	0.1914			0.6455	4.3511	0.4196	2.1619
NYMEX			0.1168	0.3214					4.3302	17.6850		
NZX			0.0512	0.2206					0.0033	0.0157		
Reference: Other			0.0096	0.0976	0.0047	0.0688			1.0503	10.9752	0.0878	1.2749
Commodity Sector												

Agri	0.0742	0.2622	0.7248	0.4470	0.8294	0.3771	4.5986	24.2826	19.9874	45.4715	27.0834	41.1602
Energy			0.2176	0.4129	0.1706	0.3771			9.2307	35.8003	1.4086	3.6591
Livestock	0.9258	0.2622	0.0288	0.1674			16.3914	21.8880	0.8181	5.4360		
Reference: Other			0.0288	0.1674					2.2891	14.0673		
Estimation Method												
OLS	0.6292	0.4833	0.6032	0.4896	0.4739	0.5005	12.8978	30.5126	11.3523	30.9354	20.3481	43.0828
GLS	0.3685	0.4827			0.1137	0.3183	8.0922	13.9915	0	0	2.1083	6.8512
Co-integration			0.1872	0.3904					9.6585	24.0482		
ECM			0.1312	0.3379					2.9104	15.6768		
GARCH			0.0160	0.1256	0.1896	0.3929			1.8267	14.5442	1.5930	3.8635
MLE					0.1896	0.3929			0	0	3.8700	8.9145
Reference: Other			0.0448	0.2070	0.0332	0.1795			2.2521	13.8025	0.5726	3.2681
Control Variables												
Lag	0.0116	0.1071	0.3824	0.4864	0.0284	0.1666	0.3423	4.1609	16.0663	31.4072	0.4234	2.5738
Commodities	0.0290	0.1678	0.1392	0.3464	0.4028	0.4916	1.6221	11.4247	2.1623	6.5011	5.4612	9.2753
Time	0.0359	0.1862	0.0416	0.1998	0.1280	0.3348	0.5413	4.6379	0.9456	5.6938	5.7409	18.7785
Basis	0.4171	0.4934	0.0928	0.2904			2.6903	4.1030	1.9351	7.0189		
Reference: Other	0.0012	0.0340	0.2496	0.4331	0.0095	0.0971	0.0579	1.7020	9.7911	44.2504	0.1283	1.3158
Publication Characteristics												
PubYear	1993.4820	5.6928	2001.6450	10.7176	2009.9810	8.0445	41878.7800	60654.9000	64689.2700	109968.6000	57314.7200	81305.2300
Impact factor	2.9353	0.7518	2.9847	0.8364	3.4391	1.5602	59.0204	77.2182	93.4590	161.3460	69.5342	65.6019
Rank A	0.0301	0.1710	0.8768	0.3289	0.3223	0.4685	0.8776	6.5017	27.1297	54.2903	3.5703	6.4857
Rank B	0.0695	0.2545	0.0432	0.2035	0.0284	0.1666	0.6843	2.5568	3.3742	17.7252	0.4234	2.5738
Rank C	0.8343	0.3720	0.0352	0.1844	0.6351	0.4826	15.5990	22.2918	0.7741	5.5171	24.0788	42.3054
Reference: ABDC No rank	0.0660	0.2485	0.0448	0.2070	0.0142	0.1187	3.8292	23.5293	1.0473	5.0795	0.4195	3.5221
Scimago <1	0.5805	0.4938	0.8704	0.3361	0.5545	0.4982	9.1491	20.7956	27.3126	54.3858	20.7070	42.7303
Scimago <2	0.0023	0.0481	0.0448	0.2070			0.1774	3.6867	3.1695	17.3320		
Scimago >2	0.0035	0.0589			0.0142	0.1187	0.2581	4.4029			0.4279	3.7181
Reference: Scimago No rank	0.4137	0.4928	0.0848	0.2788	0.4313	0.4964	11.4054	26.0638	1.8432	7.0220	7.3572	11.0206

Source: Author's work

Table 4.6: Bayesian model regression – Price level sub-sample

This table summarizes the meta-regression analysis results of the price level sub-sample. The dependent variable of this regression is the *t* statistic of the estimated MV hedge ratio from regression *j* in study *i* (t_{ij}). Post. Mean = Posterior Mean; Post. SD = Posterior Standard Deviation and PIP = Posterior Inclusion Probability. The OLS frequentist check includes the explanatory variables with PIP>0.5 only. The standard errors in the OLS are clustered at the study level. A detailed definition of the explanatory variables are included in the Table 4.4.

	Bayesian Model Averaging (Weighted 1/SE)			OLS		
	Post. Mean	Post. SD	PIP	Coefficient	Standard Error	P value
Precision	-882.6500	113.1419	1.0000	-878.7522	21.4853	0.0000***
MidYear	0.5576	0.0652	1.0000	0.5574	0.0046	0.0000***
Daily	18.6706	2.7437	1.0000	19.2382	0.5753	0.0000***
Weekly	15.2087	2.3610	1.0000	15.6039	0.6021	0.0000***
Cross-hedge	17.8232	2.6326	1.0000	18.4749	0.7289	0.0000***
Livestock	-5.8226	1.1792	0.9989	-6.3093	0.0889	0.0000***
OLS	-4.0383	0.5411	1.0000	-4.0973	0.1902	0.0000***
Lag	-3.1565	0.6334	0.9999	-3.0711	0.5416	0.0000***
Commodities	-3.8810	0.4582	1.0000	-3.8807	0.0280	0.0000***
Time	37.5439	5.5447	1.0000	38.6951	1.1901	0.0000***
Basis	-0.7535	0.1031	1.0000	-0.7578	0.0663	0.0000***
PubYear	-0.1332	0.0170	1.0000	-0.1355	0.0094	0.0000***
Impact factor	4.9512	0.7363	1.0000	5.1460	0.1687	0.0000***
ABDC Rank A	0.4344	0.7849	0.2833			
ABDC Rank B	-9.4908	1.2571	1.0000	-9.6759	0.2414	0.0000***
Scimago (Q<2)	-37.9523	5.4650	1.0000	-39.1145	1.4355	0.0000***
(Intercept)	3.0297	NA	1.0000	3.0380	0.6619	0.0010***

Source: Author's work

Table 4.7: Bayesian model regression – Price change sub-sample

This table summarizes the meta-regression analysis results of the price change sub-sample. The dependent variable of this regression is the t statistic of the estimated MV hedge ratio from regression j in study i (t_{ij}). Post. Mean = Posterior Mean; Post. SD = Posterior Standard Deviation and PIP = Posterior Inclusion Probability. The OLS frequentist check includes the explanatory variables with PIP>0.5 only. The standard errors in the OLS are clustered at the study level. A detailed definition of the explanatory variables are included in the Table 4.4.

	Bayesian Model Averaging (Weighted 1/SE)			OLS		
	Post. Mean	Post. SD	PIP	Coefficient	Standard Error	P value
Precision	-78.4109	29.2678	1.0000	-91.7662	38.9976	0.0300**
MidYear	-0.0001	0.0023	0.0639			
Daily	0.0403	0.1107	0.1607			
Weekly	-0.0212	0.0844	0.0921			
Own-hedge	-0.0388	0.0896	0.2228			
Cross-hedge	0.0192	0.0559	0.1565			
CBOT	-0.2804	0.0921	1.0000	-0.2378	0.0657	0.0020***
CME	-1.4995	0.2172	1.0000	-1.5919	0.3933	0.0010***
ICE	-1.2039	0.4307	0.9754	-1.1109	0.4332	0.0200***
MGEX	-0.0255	0.0988	0.0982			
NYMEX	-2.0042	0.1469	1.0000	-1.9905	0.1440	0.0000***
NZX	0.2517	4.5107	0.0378			
Agri	-0.1215	0.0298	0.9930	-0.1237	0.0056	0.0000***
Energy	0.0049	0.0198	0.0894			
Livestock	-0.5703	0.0660	1.0000	-0.5724	0.0145	0.0000***
OLS	-0.0026	0.0143	0.0647			
Cointegration	-0.4250	0.0999	0.9999	-0.4655	0.1155	0.0010***
ECM	-0.0045	0.0202	0.0811			
GARCH	0.2293	0.0464	0.9995	0.2310	0.0764	0.0070***
Lag	-0.4895	0.0403	1.0000	-0.4860	0.1478	0.0040***
Commodities	-0.5336	0.1080	0.9995	-0.5265	0.1149	0.0000***
Time	-0.0029	0.0314	0.0441			
Basis	-0.0065	0.0270	0.0868			

PubYear	0.0403	0.0152	0.9228	0.0468	0.0195	0.0280**
Impact factor	-0.5646	0.0823	1.0000	-0.6032	0.1088	0.0000***
ABDC Rank A	3.8804	0.7161	1.0000	4.2281	0.9483	0.0000***
ABDC Rank B	2.6395	0.4823	1.0000	2.8611	0.6455	0.0000***
ABDC Rank C	2.7335	0.2563	1.0000	2.8432	0.3360	0.0000***
Scimago (Q<1)	-2.4560	0.3931	1.0000	-2.6328	0.5746	0.1680
Scimago (Q<2)	-1.0763	0.4785	0.8987	-1.2446	0.8654	0.4890
(Intercept)	-0.5258	NA	1.0000	-0.6282	0.8901	0.1360

Source: Author’s work

Table 4.8: Bayesian model regression – Return sub-sample

This table summarizes the meta-regression analysis results of the price change sub-sample. The dependent variable of this regression is the *t* statistic of the estimated MV hedge ratio from regression *j* in study *i* (t_{ij}). Post. Mean = Posterior Mean; Post. SD = Posterior Standard Deviation and PIP = Posterior Inclusion Probability. The OLS frequentist check includes the explanatory variables with PIP>0.5 only. The standard errors in the OLS are clustered at the study level. A detailed definition of the explanatory variables are included in the Table 4.4.

	Bayesian Model Averaging (Weighted 1/SE)			OLS		
	Post Mean	Post SD	PIP	Coefficient	Standard Error	P value
Precision	-255067.4002	55870.9440	1.0000	(omitted)	(omitted)	
MidYear	0.0155	0.0054	1.0000	0.0161	0.0060	0.0250**
Daily	-15949.1673	30511.4693	1.0000	0.7176	0.2391	0.0150**
Weekly	-35147.8476	79073.9732	1.0000	0.1305	0.5230	0.8090
Own-hedge	-0.0125	0.1389	1.0000	-0.0172	0.1952	0.9320
Cross-hedge	0.0000	0.0000	0.0000			
CBOT	-0.2272	0.2862	1.0000	-0.1902	0.0999	0.0890*
CME	52770.7545	112254.0969	1.0000	(omitted)	(omitted)	
ICE	-0.3863	0.2931	1.0000	-0.3395	0.1463	0.0450**
LIFFE	-0.2797	0.2866	1.0000	-0.2455	0.1001	0.0370**
MATIF	-0.2699	0.2883	1.0000	-0.2714	0.1280	0.0630*
MGEX	-0.2939	0.3441	1.0000	-0.1857	0.0759	0.0370*
Agri	-0.1530	0.2274	1.0000	-0.1895	0.1055	0.1060
OLS	286.0275	51.3854	1.0000	0.1346	0.1423	0.3690
GLS	286.0733	51.3851	1.0000	0.1683	0.1013	0.1310
GARCH	34718.7257	79030.2720	1.0000	-0.5223	0.3300	0.1480
ML	286.2145	51.3813	1.0000	0.3264	0.0810	0.0030***
Commodities	-0.7850	0.0510	1.0000	-0.8041	0.1275	0.0000***
Time	0.0000	0.0000	0.0000			
PubYear	142.9131	25.6893	1.0000	-0.0160	0.0059	0.0240**
Impact factor	-12567.8311	26529.1992	1.0000	-0.0232	0.1427	0.8740
ABDC Rank A	58907.8675	125781.2919	1.0000	0.8673	0.4667	0.0960*
ABDC Rank C	19391.0723	41792.6138	1.0000	0.4089	0.0533	0.0000***
Scimago (Q < 1)	-15650.0371	33609.7185	1.0000	0.1176	0.0994	0.2670
Scimago (Q> 2)	30307.4668	62826.7925	1.0000	0.3238	0.8448	0.7100
(Intercept)	0.5018	NA	1.0000	0.9754	3.2212	0.7690

Source: Author's work

Chapter Five

Conclusion

In this thesis, I have conducted three studies that are linked together in that they investigate three different aspects of the financialization process in agricultural commodity markets. The first study examines the performance of a newly introduced financial instrument regarding commodities and the impact of its design characteristics on performance. The second study investigates the suitability of introducing a derivative product on a new agricultural commodity. The third study examines the extent to which the use of existing futures contracts on commodities would achieve the objectives set by the regulators.

The first study investigates the time-varying nature of the tracking performance of ETCs using the MS regression model. Due to the uniqueness of the sample and the depth of the analysis, this study adds novel evidence to a narrowly researched area within agricultural commodity markets. The findings of the study support the view that agricultural ETCs do not replicate the underlying index precisely during high-volatility periods compared with low-volatility periods. However, this difference in the tracking performance is not persistent over time. In addition, the characteristics of an ETC, such as replication method and leverage, also affect the tracking performance of agricultural ETCs. These findings have practical importance for both ETC issuers and investors. If the characteristics of an ETC lead to inefficient tracking performance, the ETC issuers are required to pay attention when they design the structure of these funds. Concurrently, investors need to be cautious, as the findings show that ETCs do not provide the promised return when the agricultural commodity markets are in turmoil.

The second study investigates the question of the suitability of introducing tea as a commodity into the financial market. This chapter provides a detailed explanation about the oldest and well-organized tea market in Sri Lanka. According to the findings, introducing a futures contract on tea may be possible to achieve, but it will be challenging under the existing market structure. The move towards the financialization of tea requires setting a standard grading system for tea, automating the auction process, educating tea market participants about the purpose and uses of a futures contract and, most importantly, changing bureaucratic attitudes of tea market participants in order to welcome this transformation. Nevertheless, tea will not be an attractive investment asset in a portfolio of an average investor. This fact will make it harder to attract speculators into this market if a tea futures contract is introduced.

The third study discusses a research question that would impact all commodity markets, not just on agricultural commodity markets. This study aims to provide empirical evidence to justify the appropriateness of the hedging effectiveness criteria set by the accounting standards. Any firm trading derivative contracts on commodities in order to hedge their price risk has to meet the threshold level of hedging effectiveness to be able to qualify for hedge accounting. This cut-off level differentiates derivative trading between hedging and speculation. I have conducted a meta-analysis in order to provide empirical evidence to justify this threshold level of hedge effectiveness in the accounting standard. Based on the findings, I propose policy makers consider changing this optimal hedge effectiveness level and setting different threshold levels based on the type of asset and the type of hedging.

To conclude, it is important to undertake further research on different financialization aspects of the agricultural commodity market as this market is rapidly evolving. The novel empirical evidence will contribute to the reshaping of the structure of this emerging market while providing valuable insights for market participants. Analysing the impact of climate change on agricultural commodity markets, examining the linkage between climate change, food security and agricultural markets and analysing the impact of climate change on agricultural trade are some possible further research topics in this area. My final objective is to continue conducting research on agricultural commodity markets to support policy makers and investors to better understand the financial products on agricultural commodities and support them in their decision-making process.